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# Target detection of ISAR data by principal component transform on co-occurrence matrix

Mousumi Gupta [a,*], Debasish Bhaskar [b], Rabindranath Bera [b], Sambhunath Biswas [c]

[a] Department of Computer Science and Engineering, Sikkim Manipal Institute of Technology, Majitar, Rangpo, Sikkim 737132, India
[b] Department of Electronics and Communication, Sikkim Manipal Institute of Technology, Majitar, Rangpo, Sikkim 737132, India
[c] Machine Intelligence Unit, Indian Statiscal Institute, 203 Barrackpore Trunk Road, Kolkata 700035, India

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ABSTRACT

Issue of automated target detection in ISAR can be stated as what features enhance objects of interest from the rest of the data. Much experimentation done in this area have used Fourier transforms for preprocessing the raw signal data. Generally the ISAR data are comes with a matrix of complex number values and therefore intuitive logic appears to favor a Fourier transform. A hypothesis was made that a Fourier transform in preprocessing may mask some data that could be part of feature used to threshold the object from background. Thus a trial was done on MATLAB simulated ISAR data to see if such data can be transformed into a matrix to visualize objects by preprocessing with principle component transform followed by some modification conventional thresholding techniques i.e. gray level co-occurrence matrix. Since it would be difficult to do so in complex valued matrices, these matrices had been decomposed to real valued and the imaginary valued matrices separately. Advantages of simulated data were that variables could be defined and changes in preprocessing transform and thresholding result could be compared with significant accuracy before a trial with actual performance of ISAR imagery. The preliminary result in this paper does show that preprocessing transform need not be Fourier. Principle component transform may bring about features that enhance thresholding values for Automatic target detection. Thresholding in conventional methods is done by finding a fixed value to create a binary image highlighting the object. In the modification proposed here single value thresholding objects and then spatially locating the object in a binary matrix may circumvented.



## 1. Introduction

Target detection is essential for target interpretation and analysis in Inverse Synthetic Aperture Radar (ISAR) imaging system. In ISAR, the target rotates and the radar is stationary and the target images can be obtained by transmitting wideband signals, and high cross range resolution is obtained by coherently accumulating number of echoes from different aspect angles. The goal of ISAR imaging system is to detect the targets particularly for surveillance. The conventional target detection system for ISAR images consists of the following stages: fast time filtering, slow time filtering, compression and decompression for focused FFT and IFFT response, Anti-aliasing and Matched Filtering. This paper proposed an algorithm for target detection for ISAR images which is based on co-occurrence matrix. Co-occurrence matrix is the statistical approach for texture representation and first introduced by Haralick et al. using the grey level co-occurrence matrix (GLCM) (Haralick et al., 1973). Co-occurrence matrix has been used to extract structural similarities between the objects (Mita et al., 2008; Jing Yi Tou et al., 2009), for classification (ZHU Le-Qing, 2010) and for segmentation (Corneloup, 1996). Co-occurrence matrix method also used by Clausi and Jerniganl (1998), where they proposed an improvement on the GLCM by presenting a grey level co-occurrence linked list (GLCLL) structure that stores the non-zero co-occurring probabilities in a sorted linked list. Rignot and Kwok (1990) have analyzed SAR images using texture features computed from gray level co-occurrence matrices. Threshold has been determined by using entropies, global, local and joint from co-occurrence matrix (Park et al., 2011; Mark et al., 1995; Chang et al., 1994).

A co-occurrence matrix captures the spatial dependence of contrast values, depending on different directions and distances specified. For a given matrix A with spatial dimension $m \times n$ with L gray levels $G = 1,2,3,\ldots,L$. The gray levels of co ordinate $(x,y)$ is denoted by $A(x,y) \in G$, the co-occurrence $C$ of $A$ is an $L \times L$ matrix

$$C = [f_{ij}]_{L\times L} \tag{1}$$

which contains the transition of gray levels with its adjacent gray levels. For the gray levels $(i,j)$ the $(i,j)$th entry of the co-occurrence matrix $C$, $f_{ij}$ is defined as

* Corresponding author. Tel.: +91 9474773860.
*E-mail addresses:* mousmi_gt@yahoo.co.in (M. Gupta), debasishbhaskar@gmail.com (D. Bhaskar), bera50@gmail.com (R. Bera), sambhu@isical.ac.in (S. Biswas).

$$f_{ij} = \sum_{i=1}^{n}\sum_{i=1}^{m}\sigma(m,n) \quad (2)$$

$\sigma(m,n) = 1$ if $\{f(m,n) = i, f(m,n+1) = j$ and/or $f(m,n) = i, f(m+1,n) = j$ $\sigma(m,n) = 0$ otherwise

The probability of the occurrence is defined as

$$p(i,j) = \left[\frac{f_{ij}}{\sum f_{ij}}\right] \quad (3)$$

As such, the co-occurrence matrix can better expose the underlying nature of texture than can a Fourier description. This is because the co-occurrence measures spatial relationships between brightness, as opposed to frequency content. This clearly gives alternative results.

Many feature vectors has been computed from GLCM (Haralick et al., 1973; Tuceryan and Jain, 1998). Falconer et al. (2006) measured the power spectral density (PSD) of a variety of objects and used the differences in the shaping of the PSD (kurtosis and energy band) to differentiate between targets and infer the activity level (i.e., resting versus moving) of human targets. Sabatini and Colla (1998) used wavelet transforms to remove the high-frequency components and reconstruct the signal; the error between the original and reconstructed signals was then used to compute a threshold for discriminating between targets. López-Estrada and Cumplido (2009) used co occurrence matrix to evaluate the cluttered environment in a given image.

In detection module, firstly the raw data are processed for target detection by using co-occurrence matrix of the gray scale image. Principal component transform (PCT) using covariance has been done by taking co-occurrence matrix as input. Furthermore,it has been noticed that after applying the proposed method number of targets presents in the environment are clearly identified.

The paper is organized as follows; In Section 2 Methodology for capturing and preprocessing of ISAR data and algorithm for target detection has been given. Section 3 represents with all the results and discussion. Finally, conclusions are included in Section 4.

## 2. Methodology

In ISAR the target motion provides the changes in relative velocity that cause different Doppler shifts to occur across the target Skolnik, 2001. The images in ISAR are generally obtained by the range-Doppler algorithm based on the 2-D Fourier transform (Fig. 1). The received RADAR signals from targets are always superposed with the receiver noise and other disturbing signals. These disturbing signals are always randomly fluctuating due to the nature of their origin. RADAR targets are very complex and composed of multiple single reflection centers. The movement of the targets results in varying phase relationships of the partial echoes from the multiple complex reflection elements. The superposition of all these partial echoes yields therefore a fluctuating resultant target echo.

The main task of the RADAR system is the detection of targets. That is for each resolution cell in space we have to decide whether a target is present or not. This task cannot be performed with absolute certainty because of the fluctuating nature of the signal. We want to reduce the false positivity. In this paper we provide a methodology where the targets are recognized after principal component transform on cooccurrence matrix. The raw data captured by the RADAR are preprocessed. The principal features after Principal Component Transform on co-occurrence matrix gives some information of the targets present in the given RADAR data. If we do directly Principal Component Transform on the raw data captured by the RADAR sometimes it does not works well.The variables which are not correlated are those that are commonly neglected. So to extract target information correctly we first evaluated co-occurrence matrix which will correlate the data. To get individual target information it is required to determine the uncorrelated data. So at second stage we have done Principal Component Transformation to determine the uncorrelated data on that co-occurrence matrix. Fig. 2 shows the steps for this proposed methodology.

### 2.1. Capturing and preprocessing of ISAR data

Cross range resolution considered for experimentation is 90 cm i.e. $\Delta R_{cross}$=90 cm. Two flat plates P1 and P2 has been taken where P1 has the dimension (1 m × 1 m) and P2 has the dimension (56 cm × 56 cm) and the step of angular rotation evaluated from the relation $S = r \times \Delta\theta$. Where r (in meter) = radial distance of the Hotspot from the central axis of rotation, $\Delta\theta$ = Step of angular rotation (in Degree) and $S$ = Arc Length for a very small $\Delta\theta$. This length is equivalently the translated distance along the cross-range for the small angular rotation of $\Delta\theta$.

To get the output image, flat plates are placed at cross-range 90 cm apart from each other, the rotation has been made in such a way so that after each rotation, RADAR can apparently see the target.$S$ has been made in such a way, so that it can be comparable comparable to $\lambda$. So, the relation $S = r \times \Delta\theta = \lambda$ has been taken into consideration.

In our case,

$$\lambda_{Min} = \frac{3 \times 10^8}{2.6 \times 10^9}\ \text{m} = 0.11\ \text{m} \quad (4)$$

$$\lambda_{Max} = \frac{3 \times 10^8}{1.7 \times 10^9}\ \text{m} = 0.17\ \text{m} \quad (5)$$

$$\Delta\theta_{Min} = \frac{\lambda_{Min}}{r}\ Degree = 0.22^\circ \quad (6)$$

$$\Delta\theta_{Max} = \frac{\lambda_{Max}}{r}\ Degree = 0.34^\circ \quad (7)$$

$$\Delta\theta_{Mid} = \frac{\Delta\theta_{Min} + \Delta\theta_{Max}}{2}\ Degree = 0.28^\circ = 0.3^\circ \quad (8)$$

Each rotation for the flat plate (1 m × 1 m) has been taken by the step of 0.3°.

Total angular span of rotation $\theta$ has been evaluated by the relation $\Delta R_{cross} = \frac{\lambda}{2\sin\theta}$

$$\theta_{Min} = \sin^{-1}\frac{\lambda_{Min}}{2 \times \Delta R_{cross}}\ radians = 3.67^\circ \quad (9)$$

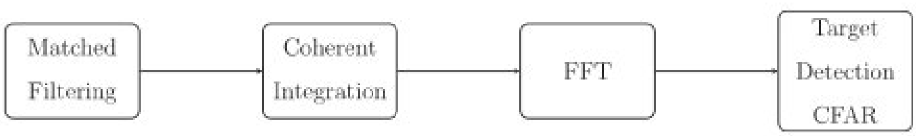


**Fig. 1.** Conventional approach for RADAR signal processing.

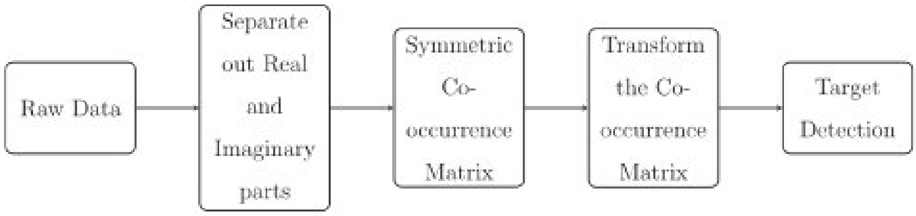


**Fig. 2.** Proposed methodology for ISAR RADAR target detection.

$$\theta_{Max} = \sin^{-1} \frac{\lambda_{Max}}{2 \times \Delta R_{cross}} radians = 6.0^{\circ} \tag{10}$$

The (56 cm × 56 cm) plate is kept fixed and the (1 m × 1 m) Flat plate is rotated starting from 23.5° to 29.5° with a step of 0.3° so that the total angular span remains 6.0°.

The flat plate (1 m × 1 m) is placed on position and rotated through its Azimuth through Midas Software; thereby observing the return power variation in S/A Mode of RTSA. At a certain Azimuth, the Elevation adjusted to observe the variation of Rx power (in dBm). Thus after each operation of orienting Azimuth and Elevation, the maximum Rx Power is taken. The position has been fixed which is at the Boresight of the (1 m × 1 m) Flat Plate.

For this (1 m × 1 m) flat plate Boresight Azimuth = 26.5° and Elevation = −5.29°. Keeping this flat plate at Boresight, the second target of dimension (56 cm × 56 cm) has been taken, which is at a cross Range distance of 90 cm but at a down range distance of 70 cm with respect to the (1 m × 1 m) Flat Plate. For the 1st angular orientation $\theta$ (=23.5°), we make a RF Carrier frequency sweep (1.7 GHz to 2.6 GHz) and capturing the 181 csv data for that particular orientation. Similarly, for 2nd angular orientation $\theta$ (=23.8°), we make a frequency sweep (1.7 GHz to 2.6 GHz) and capturing the 181 csv data for that particular orientation and so on. Thus we do the frequency sweeping operation for total 21 angular orientations ($\theta$ =23.5° to 29.5°; step = 0.3°). Thus at first we collect (181 × 21(Data type 1)) matrix data covering for all orientations.

### 2.1.1. Simulation model for generating RADAR front end data

Three point scatterers were designed by the use of MATLAB Simulink model as shown in Fig. 3.The left and right point scatterers are rotating with an angular step of 0.3° about a central axis and the middle point scatterer is stationary.

The reflected energy (as per RADAR range equation) from each of the point scatterers are merged in a single frame (of size 3 × 1) with their independent phase and magnitude values. The rear side point scatterer is placed 17 m behind the middle point scatterer and at a 0.9 m cross range distance w.r.t the right side point scatterer. This rear side point scattarer is encircled in the above Fig. 3. The cross range distance between left and middle point is 0.5 m. Similarly the middle and right points are separated in cross range by 0.5 m.

To receive data matrix through simulation model, four point scatterers (including the rear one also) are considered here. The return signal vector is received from point A as shown in Fig. 3. This signal vector is a frame of size 4 × 1 where each element is a complex number carrying the independent phase and magnitude information being reflected from each point scattarer according to RADAR range equation. After making reshape of this column frame at the RADAR receiver, it gets the dimension of a row vector of size 1 × 4. This is achieved for a particular orientation of the scattarer-assembly. As the point scattarer assembly is rotated starting from 23.5° to 29.5° with a step of 0.3°, so there will be generated 21 row vectors each of size 1 × 4. So, for a single radio frequency, a data matrix will be generated having the dimension of 21 × 4.

In practical operation, the frequency (relative frequency) is swept from 1.7 GHz to 2.6 GHz in the step of 5 MHz at a particular angular orientation of the point scatterers and the data for each frequency is collected through the MATLAB workspace. Then for next angular orientation of the point scatterer's assembly, the frequency is swept from 1.7 GHz to 2.6 GHz with a similar step size

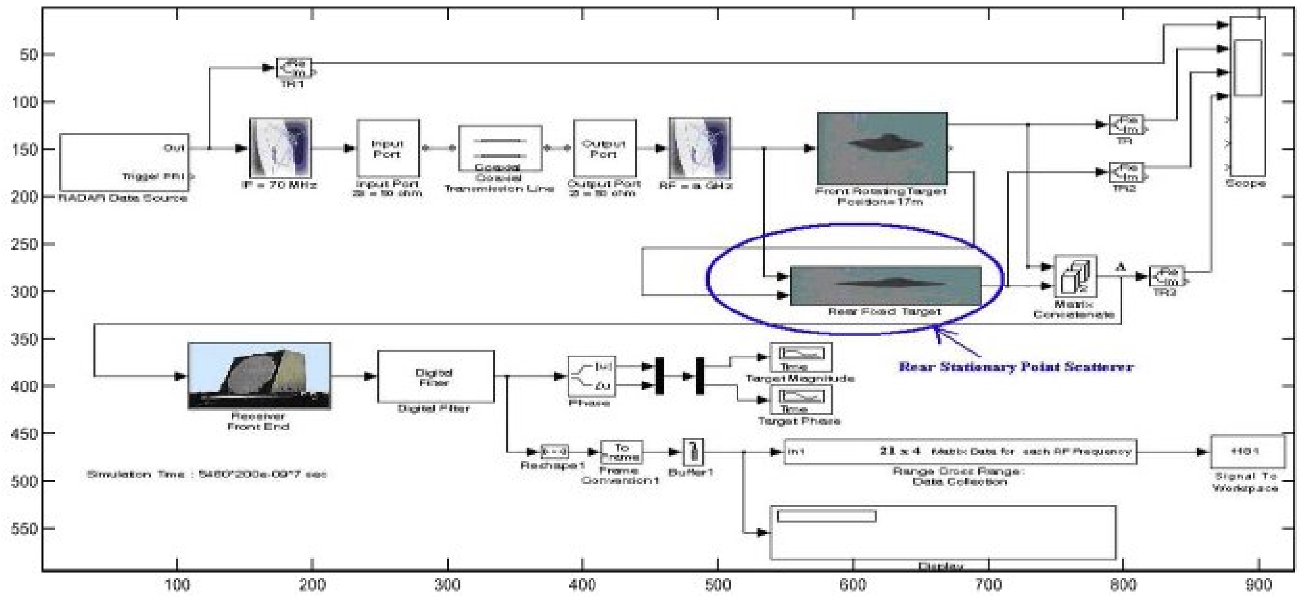


**Fig. 3.** The complete simulation for RADAR front end data generation; the rear stationary point scatterer is encircled.

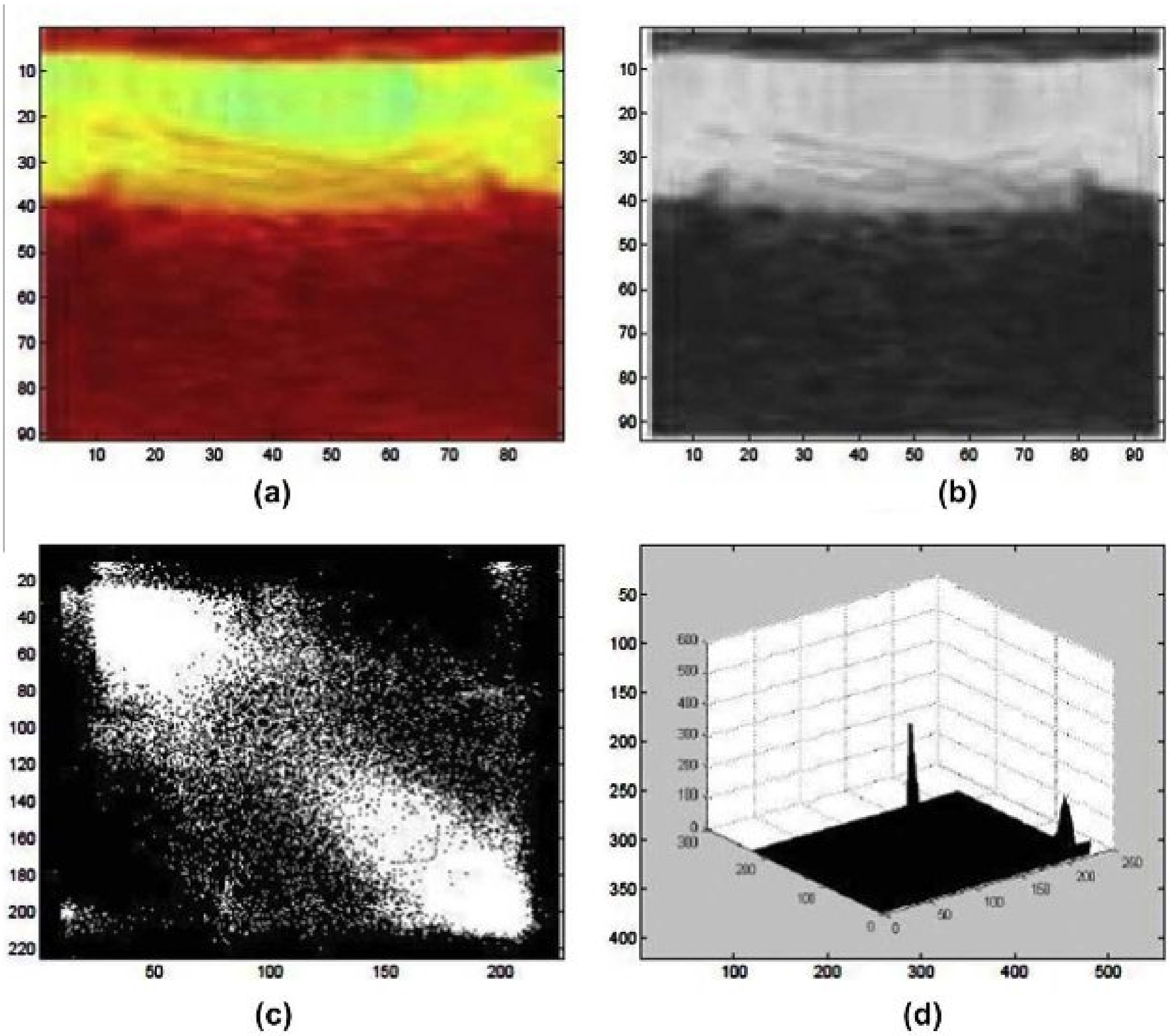

Fig. 4. (a) Image captured by processing the ISAR experimental data using conventional approach (b) gray scale image (c) co-occurrence matrix generated from gray scale image (d) surface plot after PCT on co-occurrence matrix.

and again the data is collected. The number of angular orientations considered here is 21 because the point scatter assembly has started rotation from 23.5° and ends at 29.5° with an angular step of 0.3°. The numbers of frequencies (i.e. RF) are taken as 181 because the RF sweep range is 1.7 GHz to 2.6 GHz with a step size of 5 MHz.

Finally 181 number of $21 \times 4$ data matrix will be generated through simulation model and consequently the resulting data matrix will be of dimension $(21 \times (181 \times 4))$ i.e., $21 \times 724$. This data matrix in the proposed approach is considered as simulated data type 3.

For the data type 2 the point scatterers are reduced to three only. In this case the rear point scattarer has been removed so we received a matrix of $(21 \times (181 \times 3))$ i.e., $21 \times 543$.

Data type 1 consists a single point scattarer and after processing the module, received a data matrix $(21 \times\ (181 \times 1))$ i.e., $21 \times 181$.

### 2.1.2. Principal component transform on co-occurrence

The preprocessed data are all in complex (real and imaginary) nature while captured by RADAR. Co-occurrence matrix has been evaluated separately for both the real and imaginary parts of the data. Here the co-occurrence matrix $C$ (Eq. (1)) evaluated is a symmetric matrix as the number of counts for a pair $(x_i, y_j)$ is the same as for the pair $(x_j, y_i)$.

Co-occurrence matrix is a two dimensional histogram of the number of times that pairs of intensity values occur in a given spatial relationship. It forms a summary of the sub patterns that could be formed by intensity pairs and the frequency with which they occur. The rows and columns of co-occurrence matrix separate the samples into various classes based on observed intensities. The matrix thus tabulates the frequencies of samples belonging to each class. The importance of adopting this interpretation of co-occurrence matrices is that it allows the formulation of a precise statistical measure for the amount of textural structure that is contained in any particular matrix. If pixel values changed rapidly from $(i,j)$ to $(i+1,j)$ or $(j+1,i)$, then the scatter would be high and if they do not change significantly they would cluster around the main diagonal. Therefore, if the image is noisy the scatter for co-occurrence matrix is high and if the image is less noisy then the scatter for co-occurrence matrix is low.

Our aim for this proposed approach is to distinguish targets from background. To extract target information from co-occurrence matrix it is required to recognize the principal target features. This is practically impossible to get target information from the cooccurrence matrix. Hence we need to find out covariance matrix based on the co-occurrence matrix so that it allows to formulate the principal components for target detection. Covariance matrix is evaluated here which fully describe the variation in

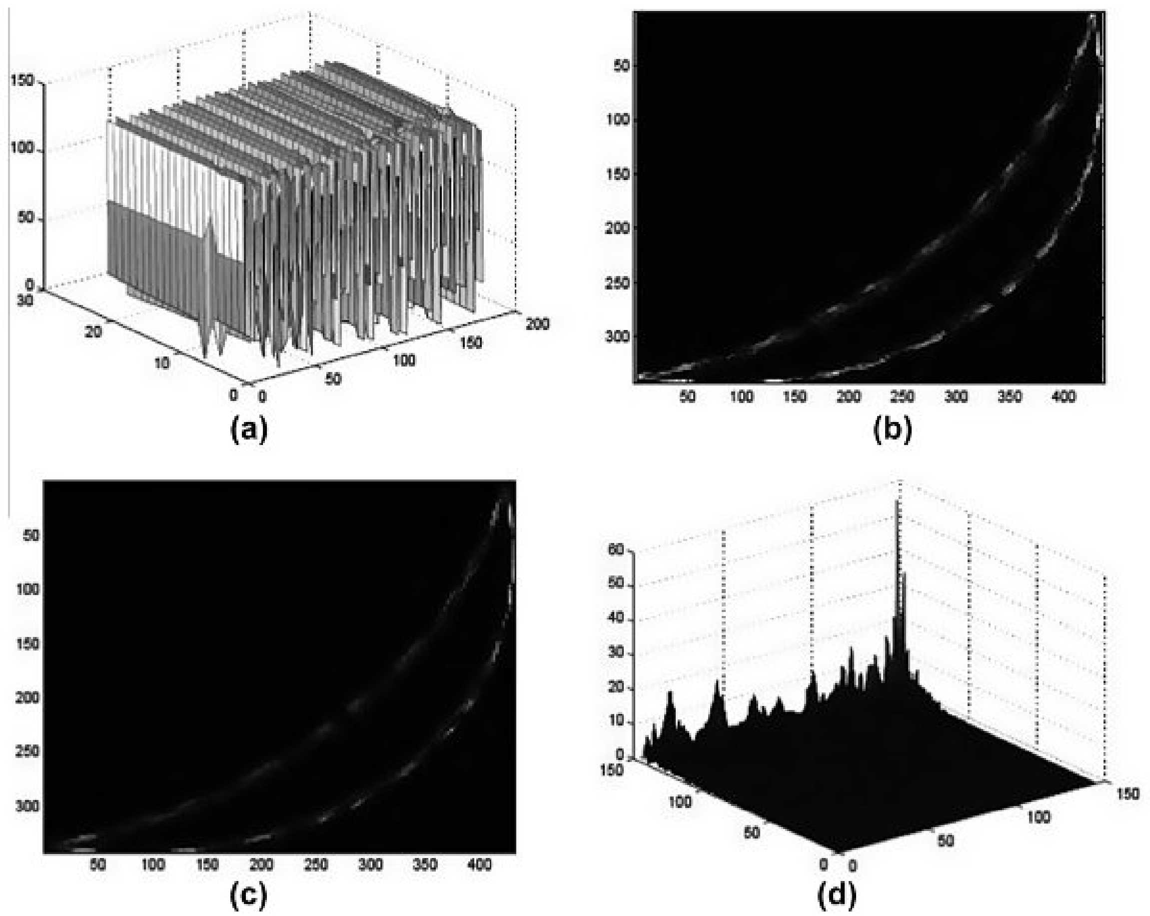


**Fig. 5.** For data type 1 (Matrix size: 21 × 181) (a) surface plot for the original data (b) co-occurrence matrix from real data (c) co-occurrence matrix for imaginary data (d) surface plot after PCT on co-occurrence matrix.

this distribution. Principal component transform completely de correlates the target and noise into two different aspects. The highest principal components where the entire information remains are represented as target. The eigenvector with highest eigenvalue is the first few principal components. By ranking the eigenvectors we are creating an ordered orthogonal basis according to the target significance. Since the eigenvector belongs to the same vector space as the co-occurrence matrix then we can say the original co-occurrence matrix simplifies its representation, by using the proposed approach, without losing much information.

Here covariance matrix describes the relative likelihood of a pattern at a particular location belonging to each class. It is then considered as belonging to the class which indicates the highest probability. Each principal component represents the greatest possible variance and each one is uncorrelated with the previously defined principal components. The first few values are the highest. Therefore the first few principal components should capture the most of the sample variation.

The mean position of the pixels in the space is defined by the expected value of the pixel vector x, and it is of value to have available means by which the scatter is described.

$$m = E(x) = \frac{1}{k}\sum_{k=1}^{k} x_k \tag{11}$$

where $m$ is the mean pixel vector and $x_k$ are the individual pixel vectors of total number. $K$ and $E$ is the expectation operator. The covariance matrix is described as $\sum_x = \frac{1}{k-1}\sum_{k=1}^{k}(x_k - m)(x_k - m)^t$. To determine the principal component transform from covariance matrix it is necessary to evaluate eigenvalues and eigenvectors of the matrix. At this stage the eigenvalues are used simply to assess the distribution of data variance over the respective components. The rapid fall in the size of eigenvalues indicates that the image data exhibits a high degree of correlation. The eigenvalues are given by the solution to the characteristic equation; $|\sum_x - \lambda I| = 0$ . Where I is the identity matrix.

The components of the eigenvectors acts as coefficients in determining the principal component brightness values for a pixel as a weighted sum of its brightnesses in the original spectral bands. The first eigenvector produces the first principal component from the original data; the second eigenvector gives rise to the second component and so on. By comparison, the variance in the last component is seen to be negligible. It is to be expected that this component will appear almost totally as noise of low amplitude. PCT transforms to a new coordinate system in the vector space in which the data can be represented without correlation. Thus the covariance matrix in the new coordinate system is diagonal. If the vectors describing the pixel point are represented byy in the new coordinate system, then it is imperative to find the linear transformation G of the original coordinates, such that $y_i = Gx = D_i^t x$ the components $y_1, y_2, \ldots y_n$ represents the variance of the pixel data in the respective transformed coordinates. It is arranged such that $y_1 > y_2 > \ldots > y_n$ so that the maximum variance represents $y_1$ and minimum variance represents $y_n$ . The components of variance with higher values are indicated as target. For testing purpose a MATLAB simulation based environment has been created and after preprocessing, the following types of data were generated;

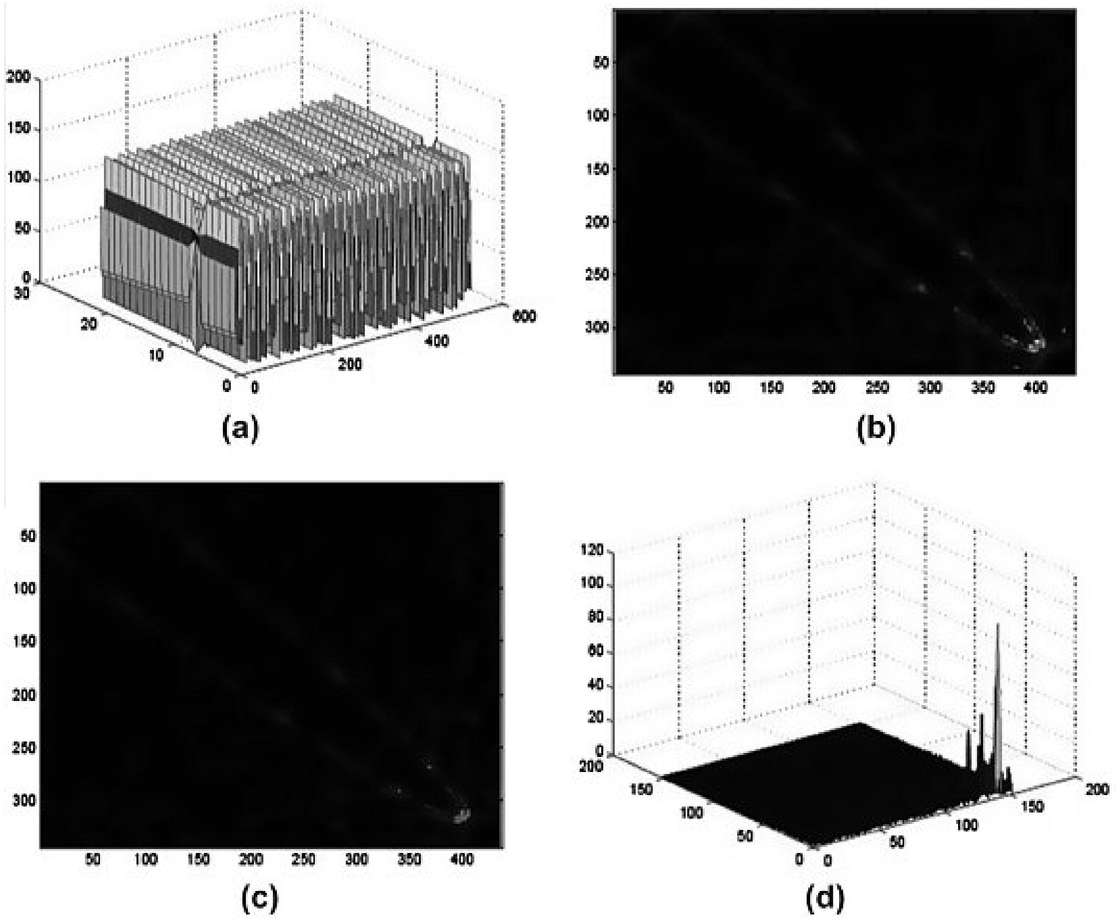


**Fig. 6.** For data type 2 (Matrix size: $21 \times 543$) (a) surface plot for the original data (b) co-occurrence matrix from real data (c) co-occurrence matrix for imaginary data (d) surface plot after PCT on co-occurrence matrix.

1. Experimental data.
2. Data type 1 (matrix size: $21 \times 181$)
3. Data type 2 (matrix size: $21 \times 543$)
4. Data type 3 (matrix size: $21 \times 724$)

## 3. Result and discussion

The received matrix size for the experimental data is $21 \times 181$.Two targets were placed in the cluttered environment. The pre-processing steps for data capturing has already been discussed in Section 2.1.The whole environment for this experiment is in a real time environment so rejection of clutter is difficult. Fig. 4(a) shows the image of the captured RADAR data after preprocessing by conventional approach. Fig. 4(c) depicts an image for probability of co-occurrence matrix which shows that there is a high correlation among the pixels of the captured image. After transforming the co-occurrence matrix with principal component transform the targets are clearly visible and can be distinguished from background. The surface plot (Fig. 4(d)) reveals two targets.

The capturing and preprocessing for data type 1, 2 and 3 in a MATLAB simulated environment are discussed in Section 2.1.1 and illustrated in Fig. 3. When there is a single target present in the cluttered environment, the generated matrix size is $21 \times 181$. Which is considered here as data type 1. Fig. 5(a) shows the surface plot for the original data where the target and background is poorly discernible. The co-occurrence matrix for real and imaginary data from data type 1 were shown in Fig. 5(b) and 5(c) respectively. After applying the proposed approach the surface plot in Fig. 5(d) display the single target.

The size of the matrix is $21 \times 543$ for data type 2 and there are three targets in the cluttered environment. The plot for original data is given in Fig. 6(a). Fig. 6(b) and 6(c) shows the images of the probability of the co-occurrence matrices. The surface plot after transforming the co-occurrence data makes the three targets apparent.

Data type 3 has the matrix size $21 \times 724$. There are four targets present in the cluttered environment. Fig. 7(b) and 7(c) shows the co-occurrence matrix for the real and imaginary data respectively. After using the proposed method, the surface plot confirm the targets which were distinguished from the background and clearly visualized in Fig. 7(d).

## 4. Conclusion

The proposed method is innovative as this a method which detects targets from cluttered environment which is not threshold dependent. By dimensionality reduction the proposed method proves its computational efficiency. Co-occurrence matrix shows the sub patterns those formed by intensity pairs and the frequency with which they occur. A transformation on co occurrence matrix has been done which extracts the principal feature components which are not dependent on any threshold selection point. These principal components were regarded as targets which are based on the strength of the probability of the occurrences. Co-occurrence matrix contains information about the correlated data while the generated covariance of this co occurrence matrix gives the

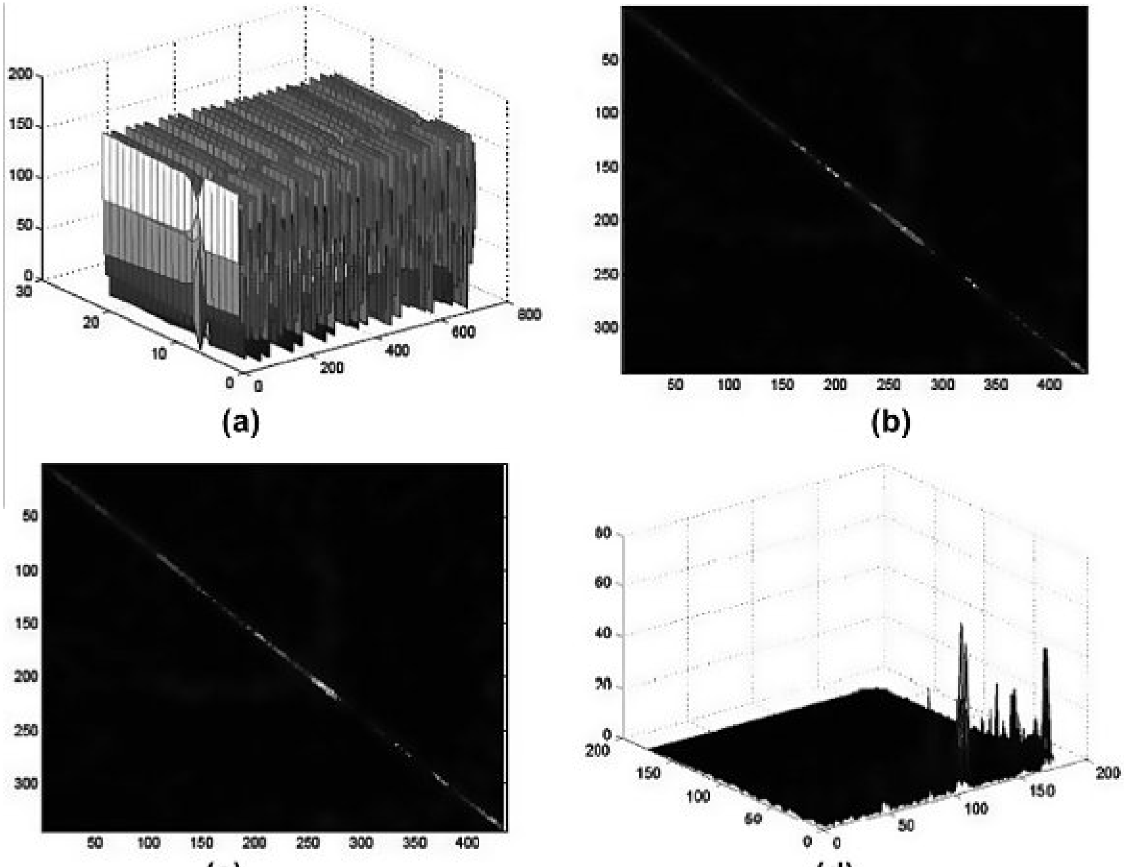


**Fig. 7.** For data type 3 (Matrix size: 21 × 724) (a) Surface plot for the original data (b) Co-occurrence matrix from real data (c) Co-occurrence matrix for imaginary data (d) Surface plot after PCT on co-occurrence matrix.

information about uncorrelated data among those correlations. Principal component transform is used to transform the correlated variables into uncorrelated variables and which reduces the dimensionality of the original data set.

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