Chapter 4

Segmentation based on Co-occurrence

PCA Transformation

4.1 Introduction on cooccurrence matrix

Image segmentation can be thought as pixel a labeling process where the pixels belonging to the same homogeneous region are assigned the same label. Previous Chapters 2 and 3 describe segmentation algorithms by down-sample and up-sample method, and Gaussian threshold selection method. These two algorithms are able to separate target and non-target regions from radar data as well as from optical data. Histogram based threshold selection techniques normally incorporate histogram information only and therefore, such algorithms may not produce good results if valleys are not truly reflected in histograms. Here, in this chapter, discussion of an algorithm is presented, which based on correlation analysis between pixels of target and non-target regions.

The issue of Automated Target Detection (ATD) in radar images can be stated as what features enhance objects of interest from the rest of the data. Experimentations, carried
out in this area, have used Fourier transform for preprocessing raw signal data. Radar data appear as a matrix of complex values and therefore, intuitive logic appears in favor of Fourier transform. In this chapter, a hypothesis has been 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 has been made on radar data, to see if such data can be transformed into a matrix to visualize objects, while preprocessing with principle component transform follows some modification on conventional thresholding techniques i.e., gray level co-occurrence matrix. Gray level co-occurrence matrix (GLCM) is the statistical approach for texture representation and was first introduced by Haralick et al.[42]. Co-occurrence matrix also has been used to extract structural similarities between objects [65] [61], for classification [57] and for segmentation [17]. Clausi and Jernigan [16] proposed an improvement on the co-occurrence matrix (GLCM) through 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 [79] have analyzed SAR images using texture features, computed from gray level co-occurrence matrices. A co-occurrence matrix captures the spatial dependence of contrast values, depending on different directions and distances.

Preliminary result shows that the preprocessing transform need not be Fourier. Principle Component Transform (PCT) may bring about features that enhance threshold values for automatic target detection. Thresholding, in conventional methods, is done by finding a fixed value to create a binary image highlighting the object. Using this modified approach, single value thresholding may spatially locate the object in a binary matrix.
4.2 Conventional approach vs proposed methodology

The conventional target detection system for SAR 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. In radar, the target motion provides changes in relative velocity that causes different Doppler shifts across the target[40]. Images in radar are generally obtained by the range-Doppler algorithm based on the 2-D Fourier transform [Fig.4.1]. The received radar signals from targets are always found to be superposed with the receiver noise and other disturbances. These disturbances 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 varied phase relationships with 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, i.e., for each resolution cell in space a decision has to be made, whether a target is present or not. This task cannot be performed with absolute certainty because of the fluctuating nature of the signal. In this chapter, radar targets were recognized after the principal component transform on cooccurrence matrix. The principal features, after application of the Principal Component Transform to the co-occurrence matrix, provides some information about the targets, present in radar images. Note that the Principal Component Transform when applied directly to raw data, sometimes may not works well. The variables which are not correlated, are those that are commonly neglected. Hence, to extract correct target information, initially the co-occurrence matrix has been evaluated to provide information about the correlation of data. To get individual target information, there is a requirement to
determine uncorrelated data. Therefore, at the second stage Principal Component Transformation is carried out to determine the uncorrelated data present in the co-occurrence matrix. Fig. 4.2 shows the steps, carried out in this proposed methodology.

![Figure 4.1: Conventional approach for radar signal processing](image1)

![Figure 4.2: Developed methodology based on co-occurrence PCA for radar target detection](image2)

### 4.3 Co-occurrence PCA transformation

A co-occurrence matrix captures the spatial dependence of contrast values, depending on different directions and distances. Let us consider a matrix $A$ with spatial dimension $m \times nc \ G = 1, 2, 3, L$. The gray level of co ordinate $(x,y)$ is denoted by $A(x,y) \in G$ and the Co-occurrence $C$ of $A$ is an $L \times L$ matrix

$$C = [f_{ij}]_{L \times L}, \quad (4.1)$$
which contains the transition of gray levels with its adjacent gray levels. For the gray levels \((i, j)\), the \((i, j)th\) entry \(f_{ij}\) of the co-occurrence matrix \(C\), is defined as

\[
f_{ij} = \sum_{i=1}^{n} \sum_{i=1}^{m} \sigma(m, n)
\]

\[
\sigma(m, n) = 1 \text{ if } \{f(m, n) = i, f(m, n+1) = j \text{ and/or } f(m, n) = i, f(m+1, n) = j\}
\]

\[
\sigma(m, n) = 0 \text{ otherwise}
\]

The probability of the occurrence is defined as

\[
p(i, j) = \frac{f_{ij}}{\sum f_{ij}}
\]

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

The co-occurrence matrix \(C\) (Eq 4.1) 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 occurred 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 frequencies of the 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 change 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 the co-occurrence matrix is high and if the image is less noisy then the scatter for the co-occurrence matrix is low.

The aim for this proposed approach is to distinguish individual targets from background. To extract target information from the co-occurrence matrix, it is required to recognize the principal target features. This is practically impossible. Thus, a covariance matrix is evaluated on the transformed co-occurrence matrix. This highlights the principal components from transformed matrix and it is used for target detection. Covariance matrix is evaluated here which fully describe the variation in 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 intact, are represented as a target. The eigenvector with highest eigenvalue is the first principal component and so on. By ranking these eigenvectors an ordered orthogonal matrix is evaluated and presented according to the target significance. Since, eigenvectors belong to the same vector space as the co-occurrence matrix, thus it can be said that, the original co-occurrence matrix simplifies its representation with 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. As the first few values are significant, they 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 helps to describe the scatter.

$$m = E(x) = \frac{1}{k} \sum_{k=1}^{k} x_k,$$  \hspace{1cm} (4.4)

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 $\Sigma_x = \frac{1}{k-1} \sum_{k=1}^{k} (x_k - m)(x_k - m)'$.

To determine the principal component transform from the 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 exhibit a high degree of correlation. The eigenvalues are given by the solution to the characteristic equation; $|\Sigma_x - \lambda I| = 0$. Where $I$ is the identity matrix. The components of the eigenvectors act as coefficients in determining the principal component brightness values for a pixel as a weighted sum of its brightness 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 the data set 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 by $y$ in the new coordinate system, then it is imperative to find the linear transformation $G$ of the original coordinates, such that $y_i = Gx = D' f x$, where the components $y_1, y_2, ..., y_n$ represent 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 \( y_1 \) represents the maximum variance and \( y_n \) represents the minimum variance. The components of higher variance values indicate the target.

### 4.4 Simulation model for generating radar front end data

#### 4.4.1 Capturing radar data through MATLAB simulation model

Cross Range Resolution considered for experimentation is 90 cm i.e. \( \Delta R_{\text{cross}} = 90 \) cm. Two flat plates P1 and P2 are considered, where P1 has the dimension (1m x 1m) and P2 has the dimension (56cm x 56cm) and the angular rotation is evaluated in steps, from the relation \( S = r \times \Delta \theta \), where \( r \) (in Meter) is the radial distance of the Hotspot from the central axis of rotation, \( \Delta \theta \) is the Step of angular rotation [in Degree] and \( S \) is the 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, 90cm apart from each other and the rotation is made in such a way that after each rotation, RADAR can apparently see the target. And, \( S \) is made in such a way that it is comparable to \( \lambda \). Hence, the relation becomes \( S = r \times \Delta \theta = \lambda \).

For this experiment;

\[
\lambda_{\text{Min}} = \frac{3 \times 10^8}{2.6 \times 10^9} m = 0.11 m \quad (4.5)
\]

\[
\lambda_{\text{Max}} = \frac{3 \times 10^8}{1.7 \times 10^9} m = 0.17 m \quad (4.6)
\]

\[
\Delta \theta_{\text{Min}} = \frac{\lambda_{\text{Min}}}{r} \text{ Degree} = 0.22^\circ \quad (4.7)
\]
\[ \Delta \theta_{Max} = \frac{\lambda_{Max}}{r} \text{ Degree} = 0.34^\circ \]  

\[ \Delta \theta_{Mid} = \frac{\Delta \theta_{Min} + \Delta \theta_{Max}}{2} \text{ Degree} = 0.28^\circ = 0.3^\circ \]  

Each rotation for the flat plate (1m X 1m) is made through a step of 0.3\(^\circ\) and the total angular span of rotation, \( \theta \) is evaluated through the relation \( \Delta R_{\text{cross}} = \frac{\lambda}{2 \sin \theta} \).

\[ \theta_{Min} = \sin^{-1} \left( \frac{\lambda_{Min}}{2 \times \Delta R_{\text{cross}}} \right) \text{ radians} = 3.67^\circ \]  

\[ \theta_{Max} = \sin^{-1} \left( \frac{\lambda_{Max}}{2 \times \Delta R_{\text{cross}}} \right) \text{ radians} = 6.0^\circ \]

The (56\(cm \times 56\)\(cm\)) plate is held fixed and the (1\(m \times 1m\)) flat plate is rotated starting from 23.5\(^\circ\) to 29.5\(^\circ\) with a step change of 0.3\(^\circ\) so that the total angular span remains fixed at 6.0\(^\circ\).

The flat plate (1\(m \times 1m\)) is placed in its 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 is adjusted to observe the variation of Rx power (in dBm). Thus, after each operation of orienting azimuth and elevation, the maximum Rx power is noted down. The position has been fixed which is at the Bore-sight of the (1\(mx1m\)) flat plate. The noted Bore-sight azimuth=26.5\(^\circ\) and elevation=-5.29\(^\circ\). Keeping the flat plate at Bore-sight, the second target of dimension (56\(cm \times 56\)\(cm\)) is considered, that is at a cross range distance of 90\(cm\) but at a down range distance of 70\(cm\) with respect to the (1\(m \times 1m\)) flat plate.

For the first angular orientation of \( \theta \) (=23.5\(^\circ\)), the RF carrier frequency sweep (1.7 \(GHz\) to 2.6 \(GHz\)) and capture 181 csv data for that particular orientation.

Similarly, for the second angular orientation of \( \theta \) (=23.8\(^\circ\)), the RF frequency sweep (1.7
GHz to 2.6 GHz) and capture 181 csv data for that particular orientation and so on. So, In this simulated model, the frequency sweeping operation is developed for 21 angular orientations ($\theta = 23.5^\circ$ to $29.5^\circ$; step = $0.3^\circ$). By this method the first data captured is of size $181 \times 21$ after covering all orientations and named here as, Data type 1.

### 4.4.2 Designing of simulation model

Three point scatterers were designed by MATLAB Simulink model as shown in Fig.4.3. Left and right point scatterers are made to rotate with an angular step of $0.3^\circ$ about a central axis, while the middle point scatterer is held stationary. The reflected energy (as per RADAR Range equation) from each of the point scatterers is merged in a single frame (of size $3 \times 1$) with their independent phase and magnitude values. The rear side point scatterer is placed $17m$ behind the middle point scatterer and at a $0.9m$ cross range distance with respect to the right side point scatterer. This rear side point scatterer is encircled in the Fig. 4.3. The cross range distance between Left and Middle point is $0.5m$. Similarly the Middle and Right points are separated in cross range by $0.5m$.

![Figure 4.3: The complete simulation for radar front end data generation; The Rear stationary point Scatterer is encircled.](image)
To receive data matrix through the simulation model, four point scatterers (including the rear one also) have been considered. The return signal vector is received from point A as shown in Fig.4.3. This signal vector is a frame of size $4 \times 1$, where each element is a complex number carrying the independent phase and magnitude information, being reflected from each point scatterer according to radar range equation. After the reshape of this column frame at the radar receiver, it gets the dimension of a row vector of size $1 \times 4$. This has been achieved for a particular orientation of the scatterer-assembly. As the point, scatterer assembly has been rotated starting from 23.5° to 29.5° with a step change of 0.3°, to generate 21 row vectors, each of size $1 \times 4$. So, for a single radio frequency, a data matrix that is generated is of dimension $21 \times 4$.

In practical operation, generally the frequency (Relative Frequency) is varied from 1.7 GHz to 2.6GHz in step of 5MHz at a particular angular orientation of the point scatterers and the data for each frequency is collected through the MATLAB workspace. For the next angular orientation of the point scatterer assembly, the frequency is varied from 1.7GHz to 2.6GHz with a similar step size 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°. RF frequency counts are 181 because the RF sweep range is 1.7GHz to 2.6GHz with a step size of 5MHz.

Finally, 181 dataset has been received with size $21 \times 4$ data matrix as generated through the simulation model and consequently, the resulting data matrix is of dimension $[21 \times (181 \times 4)]$ i.e., $21 \times 724$. This data matrix is considered here as data type 3.

For the data type 2, the point scatterers are reduced to three only. In this case, the rear point scatterer is removed and receive another set of matrix with size $[21 \times (181 \times 3)]$ i.e., $21 \times 543$. 

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Data type 1 consists a single point scatterer and after processing the module, there is a data matrix of \([21 \times (181 \times 1)]\) i.e., \(21 \times 181\) size.

For testing purpose, a MATLAB simulation based environment has been created and after preprocessing, the following types of data were generated:

1. Experimental data
2. Data type 1 (Matrix size: 21 X 181)
3. Data type 2 (Matrix size: 21 X 543)
4. Data type 3 (Matrix size: 21 X 724)

In the simulated model, preprocessed data are all complex (real and imaginary) and the co-occurrence matrix is evaluated separately for both the real and imaginary parts of the data.

4.5 Results and discussion

The main objective, for the development of this method, is to extract target and non-target regions separately. Since, in case of SAR images, both target and non-target regions overlap, separation of these two regions is difficult and the result for true target classification is always based on how much separation is made to distinguish between target and non-target regions. The co-occurrence PCA method is able to un-correlate these two information from a given set of SAR images.

4.5.1 Results with SAR data

The method is tested on SAR (MSTAR images) data, optical images and simulated captured radar data. In section 4.4.2, the simulated model has already been discussed. First
part of this section discusses the output for SAR images. The SAR images considered in this chapter were: BTR60 (armored car), 2S1 (cannon), D7 (bulldozer), BRDM2 (armored reconnaissance vehicle), T62 (tank) and SLICY (stationary structure). It is noticed that, the developed method works significantly well for distinguishing between target and non-target regions. In Fig. 4.4, the transformed image contains only one peak and this peak can be considered for further classification. The output is the same for Fig.4.5, 4.6 and 4.7. In Fig.4.6, the transformed output image contains two peaks where as in the given image, there is only one target. Therefore, a conclusion can be made, that the output contains one single true target and another peak represents false target. Fig. 4.7 is the image for BRDM2. Which is a armored reconnaissance vehicle. The image is totally dominated by clutter and is difficult to distinguish between target and non-target regions. The output image in this figure contains three peaks. Therefore, here a conclusion can be made that there are two false targets. As per the classification theory, these false targets can be recognized by robust classifier.

Figure 4.4: Co-occurrence PCA transformation on BTR60
Figure 4.5: Co-occurrence PCA transformation on 2S1

Figure 4.6: Co-occurrence PCA transformation on D7
Figure 4.7: Co-occurrence PCA transformation on BRDM2

Figure 4.8: Co-occurrence PCA transformation on T62
4.5.2 Results with simulated radar data [36]

The data, captured through the simulation model, has complex values. Next, these data matrices are decomposed to real valued and the imaginary valued matrices separately. Advantages of simulated data are that variables can be defined and changes in preprocessing transform and thresholding result can be compared with significant accuracy before a trial with actual performance of radar imagery.

The received matrix size for the experimental data is $21 \times 181$. Two targets were placed in the cluttered environment. The environment for the experiment is in real time. As a result, the rejection of clutter is difficult. Fig.4.10(a) shows the image of the captured RADAR data after preprocessing by conventional approach. Fig.4.10(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.4.10(d)) reveals two targets.

Figure 4.10: (a) Image captured by processing the radar experimental data using conventional approach (b) Gray scale image (c) Co-occurrence matrix generated from gray scale image (d) Surface plot for co-occurrence PCA transformation

The capturing and preprocessing for data type 1, 2 and 3 in a MATLAB simulated environment are discussed in section 4.4.2 and illustrated in Fig.4.3. 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.4.11(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. 4.11(b) and 4.11(c) respectively. After applying the proposed approach the surface plot in Fig. 4.11(d) displays 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. 4.12(a). Fig. 4.12(b) and 4.12(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. 4.13 (b) and 4.13 (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. 4.13(d).
Figure 4.11: For data type 1 captured by simulated model (Matrix size: $21 \times 181$) :
(a) Surface Plot for the original data (b) Co-occurrence matrix from real data (c) Co-occurrence matrix for imaginary data (d) Surface plot for co-occurrence PCA transformation
Figure 4.12: For data type 2 captured by simulated model (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 for co-occurrence PCA transformation.
4.5.3 Results with BSDS500 optical dataset

BSDS500 datasets are used for optical images. In surveillance for optical images, segmentation helps to detect target from rest of the object present in a given scene. Co-occurrence PCA transformation technique is used for segmentation of BSDS500 dataset. Here the main objective is, to provide output through two sets of values so that target and non target region can be separated without overlapping each other. The results of
segmentation shows two peaks, where one peak is for target and another is for non-target region. These two regions are further classified in next chapter. The classification result (discussed in next chapter) proves robustness of the developed technique.

Figure 4.14: Co-occurrence PCA transformation on optical images
Figure 4.15: Co-occurrence PCA transformation on optical images

Figure 4.16: Co-occurrence PCA transformation on optical images
4.6 Conclusion

It is surprising to note that this method can easily distinguish the targets and background (non target region) components from the cluttered dominated environment. Another interesting feature for this method is, its threshold independent nature. 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. PCA transformation on co-occurrence matrix significantly extracts the principal feature components which are not dependent on any threshold selection point. The principal components are regarded as peaks. These peaks represent the targets. In the proposed algorithm, co-occurrence matrix contains information about the correlated data while the generated covariance of this co-occurrence matrix gives information about uncorrelated data among those correlations. PCA transformation reduces the dimensionality for original data set and it shows efficiency of the developed approach. Robustness is proved when the same algorithm applied on different types of data other than standard dataset. Same algorithm is applied for simulated and real time radar data as well as in optical images taken from BSDS500 dataset.