Chapter 5

Hybrid approach for segmentation

5.1 Introduction for hybrid approach

The success of target detection depends on segmentation. Better the segmentation, better is the chance of target detection. Chapters 2, 3, 4 includes the description for three developed segmentation methodology. Initial approach was based on down-sample up-sample followed by matrix difference. This approach produces a smooth effect on input images and is able to reject few unwanted components. It has been tested on SAR images as well as on optical images. The down-sample up-sample approach can be used as pre processing for radar images. The 'Gaussian threshold selection' algorithm is based on threshold selection from a Gaussian fit on the image histogram. The evaluated minima points from Gaussian fit are set as threshold points for image data sets. This algorithm was also tested on SAR images and optical images. Third approach for segmentation is based on correlation analysis between the target and non-target regions. Co-occurrence PCA transformation on a given data set produces a significant output for discriminating
between the regions present in an image. This method is tested on the previous images, both SAR, optical as well as on simulated model data set on SAR. These three approaches provide good results only with some specified characteristics of clutter.

Due to heterogeneous environment conditions, radar target detection has become a challenge for most situations[104]. For radar target detection, many hybrid methodology[90] [93] have already been proposed. But none of them produce satisfactory results. In recent years, multisensor data fusion has received significant attention for target detection from radar data and optical data. These data fusion techniques combine data from multiple sensors [39] to improve accuracy. Based on this idea, a hybrid approach is developed by combining all three previously discussed methodologies. It is noticed that there are few images from MSTAR data sets and BSD500 data sets where one single approach fails to separate target and non-target regions. Hybrid approach comprises of down-sample up-sample, Gaussian threshold selection and co-occurrence KPCA (Kernel PCA) technique. In the hybrid approach, accuracy depends on the final extracted information.

Fig. 5.1 shows the block diagram for hybrid segmentation that has been developed here. As can be seen in the block diagram here the hybrid approach uses down sample up sample, Gaussian threshold selection, cooccurrence KPCA in tandem in the given order.
5.2 Hybrid segmentation technique

In radar target detection, selecting true target information is a significant task. The down-sample and up-sample is suitable for extraction of very small components (either target or non-target). SAR speckle, one of the major degrading factor for radar images, may result in poor radiometric resolution that ultimately can affect classification results [77]. These speckle depends on signal and the effect can act like multiplicative noise[58]. For this reason, SAR images always suffer from multiplicative noise. Down-sample and up-sample methodology is not always sufficient to remove these speckle effect. There are
images, where extraction of very small components is not sufficient for true target classification. The advancement of synthetic aperture radar technology with high-resolution images demands better speckle-filtering algorithms. Due to the influence of multiplicative speckle noise, SAR images are blurred on the boundaries of difference areas, and it is difficult to locate boundaries. In the hybrid technique, Gaussian threshold selection algorithm is applied after down-sample up-sample and matrix difference methodology. This algorithm segments each small components present from the difference image and is also able to reject few speckle effect. Segmentation based on Gaussian threshold selection algorithm is much better in high resolution images. In case of target detection, the ultimate goal is to maximize the margins between target class and non-target class so that the feature of target and non-target can be highlighted. Co-occurrence Kernel PCA transformation produces discrimination between different classes present in the threshold image. Co-occurrence matrix considers the spatial layout of pixel in the neighborhood and characterizes how often different combinations of values occur at a given distance \( d \) and angle \( \theta \). It can, therefore be said that co-occurrence matrix can better expose the underlying nature of texture than that a Fourier description can. The principal features after Principal Component Transform on co-occurrence matrix, gives some information of the targets present in the radar data set. If PCT (Principal Component Transform) is directly applied on raw data captured by the radar, then sometimes it does not works well. The variables, which are not correlated, are those that are commonly neglected. So, to extract target information correctly, at first co-occurrence matrix is evaluated which gives information about correlation of data. To get the individual target information, dataset is again un-correlated by carrying out Principal Component Transformation on the co-occurrence matrix.
5.2.1 Pre processing

The presence of speckle effect damages the radiometric resolution in radar captured images and it seriously affects the tasks of image analysis for target detection. So, these speckles are reduced using the down-sample up-sample approach. This step can be considered as pre processing stage of radar target detection when images are strongly dominated by clutter. This step can be viewed from the figure 5.1(block diagram for hybrid approach) as follows:

\[I_{(MXN)} \rightarrow \text{Original image}\]
\[I_{1(M/2XN/2)} \rightarrow \text{Downsample step 1}\]
\[I_{2(M/4XN/4)} \rightarrow \text{Downsample step 2}\]
\[J_{1(M/2XN/2)} \rightarrow \text{Upsample step 1}\]
\[J_{2(MXN)} \rightarrow \text{Upsample step 2}\]
\[I_{(MXN)} - J_{2(MXN)} \rightarrow D \leftarrow \text{Pre-processed Image}\]

If the pre-processed image \(D\) contains \(n\) number of pixels with gray level belonging to the set \(0,1,\ldots,L-1\). The partitioning of the image \(D\) into \(k+1\) classes can be considered as \(k\) dimensional optimization problem for \(k\) optimum threshold denoted by \(t_0, t_1, \ldots, t_{k-1}\).

5.2.2 Segmentation by threshold selection and cooccurrence KPCA

The optimum threshold points has been determined by developing ‘Gaussian threshold selection’ algorithm. In this algorithm, the histogram of \(D\) has been fit by using sequence of Gaussian equation [Eq. 3.1]. The parameters \(a, b\) and \(c\) of Eq 3.1 are adjusted by taking the condition RMSE \(\leq 10\). Threshold points are the simultaneous changes or
discontinuity in intensity levels and these points can be captured by evaluating points of inflections. So by considering this, the points of inflections are the points which separates individual regions.

Threshold images are reconstructed with co-occurrence equation[Eq. 4.1]. Coocurrence matrix can be defined as a sample of joint probability density of the gray levels of two pixels separated by a given displacement[4]. In cartesian coordinates, the displacement of the cooccurrence are selected as vector(Δx,Δy). This can be defined as [4]:

\[ N(i, j) = (#pair(i, j) \mid image(x, y) = i \text{ and } image(x + \Delta x, y + \Delta y) = j) \]

where \((i, j)\) are gray levels. Co-occurrence matrix extracts the information about correlated components. The principal features are extracted after KPCA (Kernel Principal Component Analysis) transformation on co-occurrence matrix. Initially, PCT (Principal Component Transform) is used to extract principal features from cooccurrence matrix. PCT is an orthogonal transformation of the coordinate system to describe data. For extraction of robust feature, one is interested in principal components that are nonlinearly related to input variables. Therefore, in order to generalize into non-linear case, the Kernel PCA is applied on cooccurrence matrix in hybrid approach. Kernel PCA first maps the input vectors \(x_t(t = 1, \ldots, \ell \text{ and } \sum_{t=1}^{\ell} x_t = 0)\) into a high dimensional feature space \(\phi(x_t)\) and then evaluates linear PCA into feature space, \(\phi(x_1), \ldots, \phi(x_\ell)\). The covariance matrix can be evaluated as:

\[
\mathcal{C} = \frac{1}{\ell} \sum_{j=1}^{\ell} \phi(x_j)\phi(x_j)^T 
\]

From Eq. 5.1, it is required to find Eigenvalues \(\lambda \geq 0\) and Eigenvectors \(V\) which will satisfy \(\lambda V = \mathcal{C}V\).

All the solutions of \(V\) must lie in the feature space \(\phi(x_1), \ldots, \phi(x_\ell)\). Therefore, this
may consider that:

$$\lambda (\phi(x_k).V) = (\phi(x_k).\bar{C}V) \quad \forall k = 1...\ell$$  \hspace{1cm} (5.2)

The eigenvectors $V$ can be defined as:

$$V = \sum_{i=1}^{l} \alpha_i \phi(x_i)$$  \hspace{1cm} (5.3)

The kernel representation $k$, is received by substituting Eq. 5.1 and 5.3 into 5.2;

$$K_{ij} := (\phi(x_i).\phi(x_j))$$  \hspace{1cm} (5.4)

An inner product in the feature space has an equivalent kernel in the input space and it is clear from the Eq. 5.4[81]. The nonlinearity only taken place while calculating the kernel function. The kernel function $K_{ij}$ compute a dot product in some feature space $F$. Therefore, by formulating the algorithm in $F$ using $\phi$ only in dot product any occurrence of a dot product can be replaced by using the kernel function [64]. And from the combination of Eq. 5.1 and Eq. 5.3 Eigen value problem can be solved for non zero Eigen value.

$$\ell \lambda \alpha = k \alpha$$  \hspace{1cm} (5.5)

From Eq. 5.5 it is evident, that by using the kernel tricks, Eigen values can be characterized by its corresponding $\alpha$ vectors. These $\alpha$ vectors can be used to find out the principal components. Initially $p$ non linear principal components are selected. These components captures the direction which describes a desired percentage of variance[48].

An inspection reveals that, in KPCA the number of principal components extracted can
exceed the input dimensionality. That is, if there is M observation for N variables then KPCA will find up to M Eigen values where as PCA can find N non zero Eigen values [48]. KPCA captures the overall variance of all correlated components extracted by cooccurrence matrix transformation on threshold image. In this work, hybrid approach includes cooccurrence KPCA, which provides best discriminating performance for target and nontarget region separation.

5.3 Results and discussions

In this section, the output of hybrid approach is discussed. The inputs are; MSTAR targets BTR60 (armored car), 2S1 (cannon), D7 (bulldozer), BRDM2 (truck), T62(tank), SLICY (man made structure). These input images are all dominated by clutter. Thus, it is seen that one could not produce significant result after applying a single procedure. Each SAR images chosen in this chapter are at either 15° or 17° depression angle.

5.3.1 Results with SAR images

Fig. 5.2(a) contains the SAR image for BTR60 and 5.2(b) includes the output after applying down sample upsample approach. Fig.5.2 (c) is the threshold image after applying Gaussian threshold selection algorithm on raw image, 5.2(d) includes the surface plot after cooccurrence PCA transformation on raw image. Fig.5.2(e) is the output after applying all three procedures randomly on the raw image. Similarly, Fig.5.3(a), 5.4(a), 5.5(a), 5.6(a) and 5.7(a) includes the SAR images for 2S1, D7, BRDM2, T62 and SLICY respectively. The set of images are selected in such a way where one single approach is not applicable. Fig.5.3(b), 5.4(b), 5.5(b), 5.6(b) and 5.7(b) contains the result of
down sample and up sample approach, which produces a smooth effect on these images. Threshold images after applying Gaussian threshold selection algorithm, has been displayed on Fig.5.3(c), 5.4(c), 5.5(c), 5.6(c) and 5.7(c). All these threshold images contain clutter along with the target. Cooccurrence PCA transformation on these images has been done for decorrelating clutter target information. The surface plots for these images produce multiple peaks, which were shown in Fig.5.3(d), 5.4(d), 5.5(d), 5.6(d) and 5.7(d). The objective for the hybrid approach is to display the targets as an individual peak in the final plot and this will reduces the computational time for target classification. The plot for hybrid approach has been displayed in Fig.5.3(e), 5.4(e), 5.5(e), 5.6(e) and 5.7(e).

Figure 5.2: (a) BTR 60 clutter dominated image with 15° depression angle (b) Preprocessed image after down sample and up sample (c) Threshold image after applying Gaussian threshold selection algorithm (d) Plot after cooccurrence PCA transformation (e) Hybrid approach
Figure 5.3: (a) 2S1 clutter dominated image with 17° depression angle (b) Pre processed image after down sample and up sample (c) Threshold image after applying Gaussian threshold selection algorithm (d) Plot after cooccurrence PCA transformation (e) Hybrid approach

Figure 5.4: (a) D7 clutter dominated image (b) Pre processed image after down sample and up sample (c) Threshold image after applying Gaussian threshold selection algorithm (d) Plot after cooccurrence PCA transformation (e) Hybrid approach
Figure 5.5: (a) BRDM2 clutter dominated image (b) Pre processed image after down sample and up sample (c) Threshold image after applying Gaussian threshold selection algorithm (d) Plot after cooccurrence PCA transformation (e) Hybrid approach.

Figure 5.6: (a) T 62 clutter dominated image with 17° depression angle (b) Pre processed image after down sample and up sample (c) Threshold image after applying Gaussian threshold selection algorithm (d) Plot after cooccurrence PCA transformation (e) Hybrid approach.
5.3.2 Results with BSDS500 datasets

Fig.5.8, 5.9 and 5.10 contains the optical images from BSD 500 datasets. Previous chapter (Chapter 4) includes the result for cooccurrence PCA transformation on optical images, taken from BSDS500 dataset. The result with co-occurrence PCA transformation was satisfactory with BSDS500 dataset, as in many situations it was only representing a single peak. But there are few results where cooccurrence PCA transformation produced multiple peaks and classification result may produce false target information. Hybrid approach produces significant variance between two regions (target and background) in fig. 5.8, fig. 5.9 and fig. 5.10.
Figure 5.8: (a) Optical image (b) Pre processed image after down sample and up sample (c) Threshold image after applying Gaussian threshold selection algorithm (d) Plot after cooccurrence PCA transformation (e) Hybrid approach.

Figure 5.9: (a) Optical image (b) Pre processed image after down sample and up sample (c) Threshold image after applying Gaussian threshold selection algorithm (d) Plot after cooccurrence PCA transformation (e) Hybrid approach.
5.3.3 Comparison between cooccurrence PCA and hybrid approach

A comparative analysis has been done to see the effect of changes using hybrid approach. Hybrid approach is applied to the same input images used in chapter 4 of BSDS500 dataset. The input image in fig. 4.14 and fig. 5.8 are same, i.e., they contain one single object. From the output obtained shows that hybrid approach produces only one peak where as cooccurrence PCA alone produces more than one peak. These peaks are vectors used for feeding into the classifier. Lesser the number of peaks easier it is for the classifier to recognize the object. Input images of fig 4.15, fig. 4.16 are same as fig. 5.9 and fig. 5.10 respectively. Result of these images show the effectiveness of hybrid approach. Thus, hybrid approach produces same number of peaks as the number of objects present in given input images.
5.4 Conclusion

For target detection, this thesis developed three techniques and initially, each of them works for specific kind of dataset in a particular environment. The hybrid approach can extend this range from radar to optical image target detection. The combination of down-sample up-sample, Gaussian threshold selection and cooccurrence KPCA reduces the time for recognition. Hybrid approach with cooccurrence KPCA feature produces high recognition rates, both for MSTAR and BSDS500 images. Co-occurrence matrix transformation reveals certain properties about the spatial distribution of gray levels in texture images, i.e., it produces the correlation between the pixels. Thus it can be conclude that combination of three algorithms produces a large discrimination capability between the targets and non-targets and which is the most important part for achieving good target recognition rate.