Many algorithms have been developed for classification of polarimetric SAR images. Most of them have ignored the texture information, and used the speckle covariance Whishart distribution as the basis of the classification. The most popular classifications developed for polarimetric SAR are unsupervised classification based on the Cloude-Pottier target scattering decomposition parameters; the scattering type $\alpha$, the entropy $H$ and the anisotropy $A$ [1, 4]. The $H/\alpha/A$ target scattering decomposition is firstly applied to cluster the image in several initial classes (for example 16 in [1]). The resulting clusters and their centers are then updated using iterative K-means based techniques to find the optimum position of the centers that reduce the cluster dispersion. Test statistics derived from the Wishart distribution of the covariance matrix are then finally applied for classification and segmentation of polarimetric SAR images.

However, all these Wishart based classifications and segmentations assume homogeneous speckle and texture information is ignored. Beaulieu and Touzi were the first to introduce a segmentation algorithm [2] that takes into account texture information. The K-Wishart distribution is used to model Gamma textured areas such as forests, and our hierarchical segmentation (or region growing approach) was shown to perform much better than the Wishart based segmentation in the presence of texture.

In this study, a new classification technique that takes the texture information is used. The new classification is based on the Beaulieu-Touzi K-Wishart segmentation. The most advanced clustering processes are considered to improve both the segmentation and clustering results. The image is first over-segmented to obtain a partition with a large number of segments. Small segments are then discarded (smaller than 20 pixels). Hierarchical clustering is applied upon the remaining segments (5000 to 2000 segments). The clustering process is stopped between 50 to 10 clusters (clusters of regions). The small segments are compared to these clusters and assigned to the most similar one. This produces a partition of the image (segmentation) with an appropriate number of segments and in which different sets of region can be considered to belong to different intermediate classes (clusters). By using a clustering process for the last merges, we include a classification aspect into the segmentation process. Finally, the user can examine each cluster and assigns it to one of the land cover classes of its interest.

The 2 main classes of clustering approach are iterative and hierarchical. The K-means algorithm is the best known iterative technique. Clustering is difficult when the spectral signatures of classes are complex and when the classes are not well separated. It could then be necessary to combine the contribution of different approaches to improve the results. We are exploring the utilization of the “mean shift” approach in the hierarchical clustering framework [3]. The “mean shift” approach could be presented as a generalization of the K-means technique. In the K-means, the cluster centers are update by calculating the mean values of the points belonging to the cluster. The “means shift” gives different weights to the points involved in the mean calculations. The centers and the data points itself could be updated. The “means shift” performs a gradient ascend in feature probability density space and moves data points toward probability density modes. The weighting factor is related to the local feature probability density. We have integrated this displacement of the segment means into the hierarchical clustering process. Moreover, we have integrated the distances between segments (the data points) into the weighting factor. This includes an aspect of spatial dependency into the clustering process.
The new classification method is validated for wetland classification using polarimetric Convair-580 SAR data collected over the RAMASAR Mer Bleue wetland in Ottawa, Canada

REFERENCES


