A Novel Approach for Urban Unsupervised Segmentation Classification in SAR Polarimetry

Soumydip Sarkar
Department of Electrical Engineering
Institute of Engineering & Management, Kolkata, India

Tamesh Halder
Department of Mining Engineering
Indian Institute of Technology, Kharagpur, India
haldertamesh@iitkgp.ac.in

Vivek Poddar
Department of Mining Engineering
Indian Institute of Technology, Kharagpur, India

Rintu Kumar Gayen
Department of Electronics and Communication Engineering
Institute of Engineering & Management, Kolkata, India

Arundhati Mishra Ray
Space Application Centre
Indian Space Research Organization, Ahmedabad, India

Debashish Chakravarty
Department of Mining Engineering
Indian Institute of Technology, Kharagpur, India

***Abstract* – In this study, we propose a novel unsupervised classifier for polarimetric SAR image segmentation by using Kullback-Leibler (KL) Divergence and subsequently the K-means algorithm. The K-means algorithm is used to divide the SAR data into spatial clusters based on the mutual proximity of the data points, whereas the KL Divergence or relative entropy measures the difference between one probability distribution and another. The main aim of this study is to assess the performance of classical approaches with this novel approach and provide better results for more accurate SAR image classification.**

Keywords— K-means Clustering Algorithm, Kullback-Leibler Divergence, UAVSAR, Synthetic Aperture Radar Polarimetry

I. INTRODUCTION

Detection of segmentation maps in radar images is essential for data retrieval/extraction/interpretation and SAR analysis. It is the process of assigning the label to a data sample test that shares common properties. It helps us to streamline information flow and simplify interpretation of data. Supervised and unsupervised are the two classification types. Supervised classification, requires prior information in the form of training samples, whereas clustering algorithms are used in unsupervised classification. We have used an unsupervised approach in this paper as the supervised approach requires a manually labelled dataset and is often human-biased so as to ignore intricate feature mappings.

Multi-look PolSAR images can be analyzed through Kullback-Leibler Divergence distribution method which is a type of stochastic distance test for a complex Wishart distribution. There are other stochastic distance distribution methods too which can be used in this method, for example, Bhattacharyya, Hellinger, Rényi of order β and Chi-square. The Wishart distribution is an example where unsupervised classification can be applied using K-means, which is an important clustering algorithm by applying stochastic distances as a similarity measure.

In existing methodologies, Negri et. al. mainly focused on using K-means clustering with stochastic distance [1] for performing image segmentation, but our approach differs suitably and result in better performance for evaluation metrics. In this work, we present a study about PolSAR image classification using K-means, and KL Divergence distribution method. The main aim of this study is to assess the performance of classical approaches with this novel approach and provide better results for more accurate SAR image classification.

II. KULLBACK-LEIBLER DIVERGENCE

The KL Divergence is used to measure probability distribution over the same random variable x, and is used a lot in data mining literature. The KL discrepancies are closely related to relative entropy, theory of information and discrimination information. The disparity between p(x) and q(x) probability distributions is not symmetrically measured [2]. The sum of the probability distributions is unity and both of the PDFs $p(x)$ and $q(x)$ are positive in nature. The KL Divergence also provides a measure of the estimated number of additional bits needed to code p(x) samples by using q(x) dependent code instead of p (x).

$$D_{KL}(p(x), q(x)) = \sum_{x \in X} p(x) ln \frac{p(x)}{q(x)}$$

An important point to remember about the KL divergence, is that it is not a distance measure, or symmetric and need not satisfy triangular inequality [2]. Here we have used the normalized KL Divergence to the range [0,1] with respect to the image, therefore this notation will be followed henceforth in this paper.

Algorithm 1: k-means clustering algorithm

Data: $x = \{x_1, \ldots, x_n\}$: Dataset of n unlabeled samples to be clustered
Result: $c = \{c_1, \ldots, c_n\}$: set of k centroids
Initialization {
Choose the number of clusters k
Select k random points from the dataset as centroids
}
Repeat until Convergence{
Assign all the points to the closest cluster centroid c
Recompute the centroid c of newly formed clusters
}
Convergence Criteria {
Centroids of newly formed clusters do not change
Points remain in the same cluster
Maximum number of iterations are reached
}

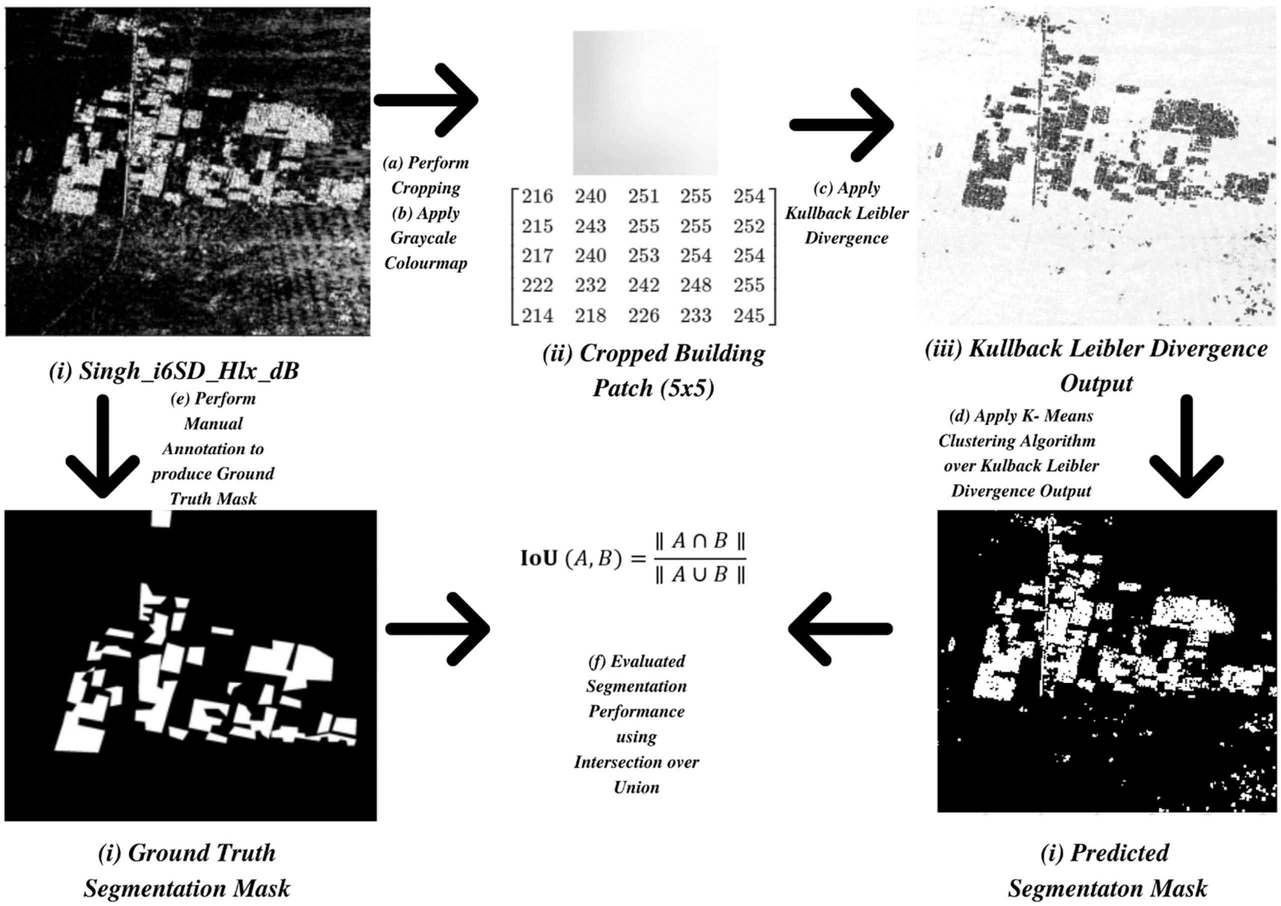

Fig. 1. Visual Interpretation of the Detailed Methodology.

III. K-means Clustering Algorithm

K-means is one of the most basic and most common unattended algorithms for learning machines. K-means' goal is simple: grouping together identical data points and finding the underlying patterns.

K-means searches a fixed number (k) of clusters in a dataset to accomplish this aim. The Scikit-Learn [4] & SciPy [5] library from Python provide very convenient modules to perform K-means clustering & KL Divergence calculations respectively, therefore, and we have borrowed the implementation for the same.

IV. Detailed Methodology

In this study, we have developed an effective method for SAR image segmentation. Our main motive is to perform segmentation using KL-divergence and K-means clustering.

A. Study Area and Dataset

The area of interest for this study is the high-resolution Urban satellite imagery for Rosamond and Hayward, which has a size of 1330x1101 and 1451x1451, respectively. The UAVSAR data for the location is handpicked for the critical performance of the proposed method and the details are mentioned in Table 1.

B. The Proposed Approach

Since the primary segmentation task for urban classification is the identification of buildings, the target is to obtaining Boolean segmentation maps. Often the unwanted/unlabelled portion of the image will be treated as the background.

Let the selected building patch be **B**, and the current window patch be **C**. The intuition behind the proposed algorithm is as follows:

- For a Non-Building Region, $D_{KL}(\boldsymbol{B}, \boldsymbol{C}) \approx 1$.
- For a Building Region, $D_{KL}(\boldsymbol{B}, \boldsymbol{C}) \approx 0$.

Due to this intra-class differentiability and inter-class similarity, the output fed to K-means algorithm, it is likely to achieve better results, since most of the pixels are saturated in a certain colour value which represents certain superpixels.

Firstly, a 5x5 cropped patch of building was taken from the Singh-Yamaguchi helix scattering (Fig. 1), and as the primary focus is to perform segmentation only on the buildings from the backgrounds, we chose the patch from a building portion itself. This 5x5 patch is now used to calculate the KL-divergence.

TABLE I. LOCATION DETAILS FOR SELECTED AREA OF INTEREST

Location	Coordinates		Region/Country	SAR Type	Description/Comments
	Latitude	Longitude			
Rosamond	34.8641° N	118.1634° W	Kern County, California, USA	UAVSAR	Urban Area consisting of Crop Vegetation Regions and Arid Hills
Hayward	37.6688° N	122.0810° W	Alameda County, California, USA	UAVSAR	Urban Area consisting of Orthogonal and Non-Orthogonal Buildings

. The original image pixel values are replaced by the calculation of the KL-divergence by convolving the 5x5 patch over the respective image. This acts like a filter applied image that is ready to be fed for clustering. This is the initial step where we prepare data before applying the K-means algorithm. Also, another cropping of a 10x10 patch was experimentally tested.

We obtained the best value of the parameter k using the elbow method for Singh-Yamaguchi helix scattering Images for K-means clustering as $k = 4$. The segmentation maps obtained can be divided into these 3 subgroups for Rosamond as shown in Fig. 2:

i. Building
ii. Hills
iii. Soil Type 1
iv. Soil Type 2

However, since we are considering only urban area classification, we will perform further analysis only for building clusters ($k = 2$). After the pre-processed KL image data is prepared, we use the K-means algorithm with k=2 clusters for (a) Buildings & (b) Backgrounds. The hyperparameters of the K-means algorithm were set as follows:

i. $\text{max\_iters} = 300$: The maximum number of iterations till the K-means algorithm converges.
ii. $\text{init} = \text{`kmeans}++\text{`}$: Initial cluster centroids initialization – optimized for convergence.
iii. $\text{n\_init} = 10$: The number of different initializations that gives the optimum inertia results.

The algorithm returns the labels that yield the best clusters that are most compact inter class and most distant intra class. Fig.1 visualizes the workflow of our methodology. Also, the KL Divergence & subsequently the K-means segmentation results obtained from the 5x5 patch are significantly better than the 10x10 patch as is clearly visible in Fig. 3-6.

C. Performance Comparison & Evaluation Metrics

A very simple yet very effective metric, Intersection over Union (**IoU**) is one of the most commonly used metrics in semantic segmentation. **IoU** is defined as the ratio between intersection (overlap) between predicted segmentation and the ground truth and union (join) between predicted segmentation and the ground truth.

$$\boldsymbol{IoU}\ (A, B) = \frac{\| A \cap B \|}{\| A \cup B \|} = \frac{Area\ of\ Intersection}{Area\ of\ Union}$$

We calculate the **Mean IoU** for binary or multi-class segmentation, by estimating the **IoU** for each class separately and finally averaging them.

Cohen's Kappa is an evaluation method that measures agreement between two reviewers for qualitative (categorical) items. In general, it is regarded as a more reliable method than simple percent agreement measurements. Mathematically,

$$\boldsymbol{k}\ (p_0, p_e) = \frac{p_0 - p_e}{1 - p_e} = 1 - \frac{1 - p_0}{1 - p_e}$$

whereas, p_0 = the relative agreement observed among raters, and p_e = the hypothetical probability of chance agreement.

Pixel Accuracy is the simplest method to evaluate an image segmentation. Consequently, we need to calculate True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values first in order to calculate the Pixel accuracy. Mathematically,

$$\textbf{Pixel Accuracy}\ (TP, TN, FP, FN) = \frac{TP+TN}{TP+TN+FP+FN}$$

The performance of each of the following algorithms is tested using the discussed Evaluation Metrics:

i. Classical K-means algorithm
ii. K-means with KL Divergence for 5x5 patch
iii. K-means with KL Divergence for 10x10 patch

The values reported for each of the approaches are drafted in Table 2.

V. FUTURE WORK

The proposed study performs binary classification, hence an extension to multiclass classification is required for a generalized methodology for improvement of semantic segmentation. A multiclass feature extraction technique using KL Divergence. Further classification includes performing orthogonal and non-orthogonal building segmentation using our proposed algorithm and also improved Polarimetric SAR change detection.

VI. Conclusion

SAR image classification via segmentation has been an active field of research and is an evolving challenge. This research successfully performs an enhanced version of the K-means algorithm using the Kullback-Leibler Divergence and achieves significantly better results over the classical K-means approach for unsupervised PolSAR Image Segmentation.

From the results, it is apparent that the proposed method gives better performance metrics for a smaller patch (5x5) than a larger one (10x10). This is possibly due to the reason that smaller patches ensure that the structured pixel values remain consistent throughout the image.

The complete code & documentation containing the methodologies discussed in this paper has been open sourced and are readily available at github.com/soumya997/kld-kmeans-segmentation-paper.

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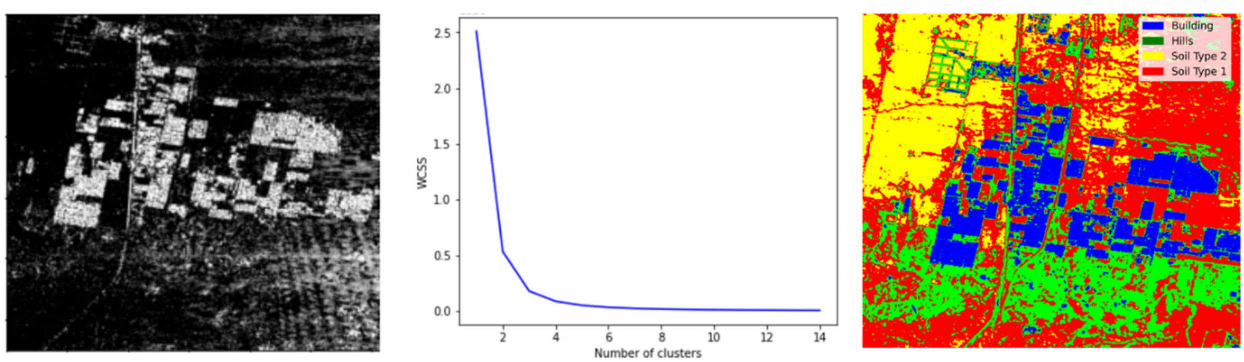
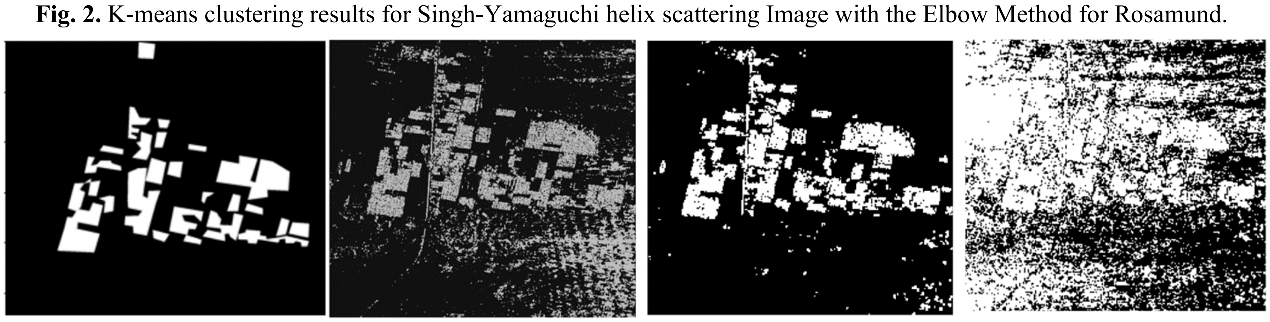
TABLE II. Performance results of the proposed methodologies via IoU metric evaluation

City	Patch size	Algorithm	Mean IOU	Kappa Score	Pixel Accuracy
Rosamond	5x5	KLD+Kmeans	0.452	0.091	0.7941
Rosamond	10x10	KLD+Kmeans	0.324	0.038	0.556
Rosamond	None	Kmeans only	0.433	0.087	0.749
Hayward	5x5	KLD+Kmeans	0.406	0.254	0.594
Hayward	10x10	KLD+Kmeans	0.33	0.182	0.5
Hayward	None	Kmeans only	0.336	0.181	0.507



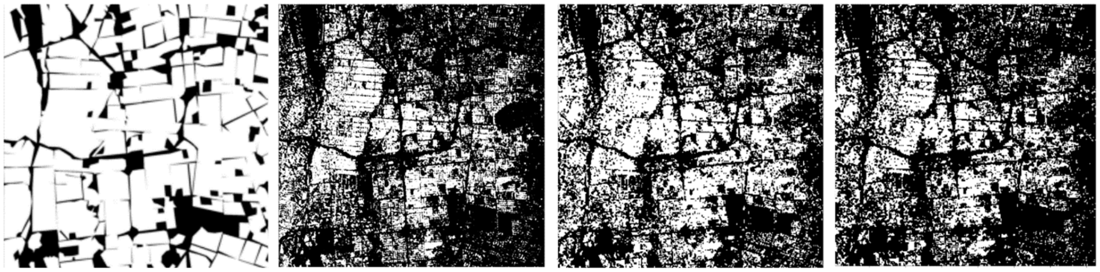
(i) Singh_i6SD_Hlx_dB *(ii) Elbow Method for k-means clustering* *(iii) k-means Clustering Results (k=4)*

Fig. 2. K-means clustering results for Singh-Yamaguchi helix scattering Image with the Elbow Method for Rosamund.



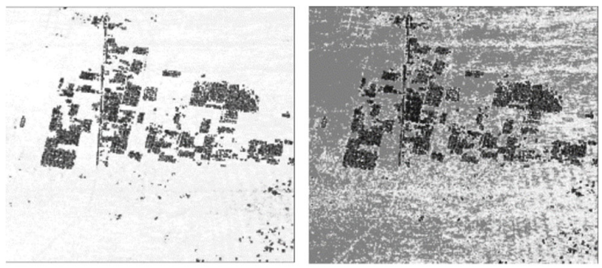
(i) Ground Truth *(ii) Classical k-means* *(iii) KL Div. with k-means for 5x5 patch* *(iv) KL Div. with k-means for 10x10 patch*

Fig. 3. Segmentation Mask Comparisons between ground truth, classical K-means and proposed method for Rosamond.



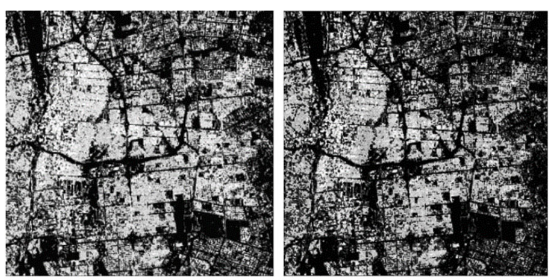
(i) Ground Truth *(ii) Classical k-means* *(iii) KL Div. with k-means for 5x5 patch* *(iv) KL Div. with k-means for 10x10 patch*

Fig. 4. Segmentation Mask Comparisons between ground truth, classical K-means and proposed method for Hayward.



(i) KL Divergence for 5x5 patch *(ii) KL Divergence for 10x10 patch*

Fig. 5. Kullback-Leibler Divergence results for different image patches for Rosamond.



(i) KL Divergence for 5x5 patch *(ii) KL Divergence for 10x10 patch*

Fig. 6. Kullback-Leibler Divergence results for different image patches for Hayward.

REFERENCES

[1] R. G. Negri, W. B. da Silva, T. S. G. Mendes, “K-means algorithm based on stochastic distances for polarimetric synthetic aperture radar image classification,” J.Appl. Remote Sens. 10(4), 045005 , 2016.

[2] S. Ranjan, D. R. Nayak, K. S. Kumar, R. Dash, and B. Majhi, “Hyperspectral image classification: A K-means clustering based approach,” in *2017 4th International Conference on Advanced Computing and Communication Systems (ICACCS)*, 2017, pp. 1–7.

[3] M. Joyce, “Kullback-Leibler Divergence,” in *International Encyclopedia of Statistical Science*, Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 720–722.

[4] X. Jin and J. Han, “K-means Clustering,” in *Encyclopedia of Machine Learning and Data Mining*, Boston, MA: Springer US, 2017, pp. 695–697.

[5] F. Pedregosa *et al.*, “Scikit-learn: Machine Learning in Python,” *J. Mach. Learn. Res.*, vol. 12, no. null, pp. 2825–2830, 2011.

[6] P. Virtanen *et al.*, “SciPy 1.0: fundamental algorithms for scientific computing in Python,” *Nat. Methods*, vol. 17, no. 3, pp. 261–272, 2020.

[7] Singh, Gulab & Yamaguchi, Yoshio. (2018). Model-Based Six-Component Scattering Matrix Power Decomposition. IEEE Transactions on Geoscience and Remote Sensing. PP. 1-18. 10.1109/TGRS.2018.2824322.