

POLSAR Image Classification via Clustering-WAE Classification Model

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POLSAR - Polarimetric Synthetic Aperture Radar

- multi-channel and multi-parameter imaging radar system
- based on AE and embedded with k-means clustering.

WAE - Wishart Auto Encoder

- used for reducing error between input and output via wishart distance
- based on auto encoder model and embedded with k-means clustering

WAE Classification Model

Wishart Distance:

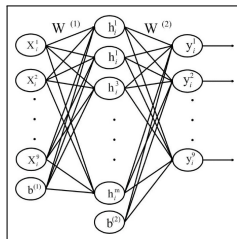
$$\min_{W,b} \frac{1}{2N} \sum_{i=1}^N d_{Wishart}(H(y_i), H(x_i)) \quad (1)$$

where,

$$d_{Wishart}(H(y_i), H(x_i))$$

= **Figure:** The structure of WAE network.

$$\text{Tr} \left(H(x_i)^{(-1)} H(y_i) \right) + \ln |H(x_i)|$$



Brief Review on AE Based Data Clustering

AE Network and K-means Clustering:

$$\min_{W,b} \frac{1}{N} \sum_{i=1}^N \|x_i - y_i\|^2$$

$$+ \lambda \sum_{i=1}^N \|f^t(x_i) - c_i^*\|_F^2$$

$$c_i^* = \arg \min_{c_j^{t-1}} \|f^t(x_i) - c_j^{t-1}\|_F^2 \quad (2)$$

Optimization:

$$c_j^t = \frac{\sum_{x_i \in C_j^{t-1}} f^t(x_i)}{|C_j^{t-1}|} \quad (3)$$

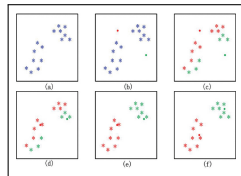


Figure: The schematic of K-means algorithm.

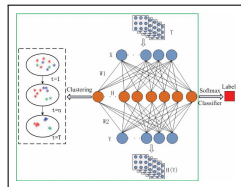


Figure: Framework of the our proposed method.

CLUSTERING-WAE CLASSIFICATION MODEL

$$\langle T_i \rangle = \begin{bmatrix} T_i^{11} & T_i^{12} & T_i^{13} \\ T_i^{21} & T_i^{22} & T_i^{23} \\ T_i^{31} & T_i^{32} & T_i^{33} \end{bmatrix}$$
$$\rightarrow x_i = [x_i^1, x_i^2, x_i^3, x_i^4, x_i^5, x_i^6, x_i^7, x_i^8, x_i^9]$$
$$(4)$$

$$\min_{W, b} \frac{1}{2N} \sum_{i=1}^N d_{Wishart}(H(y_i), H(x_i)) + \lambda \sum_{i=1}^N \|h_i^t - c_i^*\|_F^2$$
$$c_i^* = \arg \min_{c_j^{t-1}} \|h_i^t - c_j^{t-1}\|_F^2$$
$$(5)$$

Table: Detailed Steps of Algorithm

Algorithm 1: Clustering-WAE classification model

Input: The training samples $X = [x_1, x_2, \dots, x_i, \dots, x_N]$ of POLSAR image, the label of training samples: $Y = [y_1, y_2, \dots, y_i, \dots, y_N]$, the number of class K , the maximum number of iterations T .

Step1: Initialize the weights $W^{(1)}$ and $W^{(2)}$ of WAE network to get the hidden representation $H^0 = [h_1^0, h_2^0, \dots, h_i^0, \dots, h_N^0]$ of training samples X , choose 1% training sample to initialize the K cluster center $C^0 = [c_1^0, c_2^0, \dots, c_K^0]$.

while $t \leq T$ **do**

Step2: Use the improved BP algorithm of function (8) to optimize the objective function (5).

$$\min_{W, b} \frac{1}{2N} \sum_{i=1}^N d_{Wishart}(H(y_i), H(x_i)) + \lambda \sum_{i=1}^N \|h_i^t - c_i^*\|_F^2 \quad (5)$$

$$c_i^* = \arg \min_{c_j^{t-1}} \|h_i^t - c_j^{t-1}\|_F^2$$

$$\begin{aligned} W^1 &= W^1 - \alpha \left(\frac{\partial}{\partial W^1} d_{Wishart}(H(y_i), H(x_i)) + \frac{\partial}{\partial W^1} \|h_i^t - c_j^{t-1}\|_F^2 \right) \\ W^2 &= W^2 - \alpha \frac{\partial}{\partial W^2} d_{Wishart}(H(y_i), H(x_i)) \end{aligned} \quad (8)$$

Step3: With the Clustering-WAE network, we could obtain the hidden representations H^t of training samples, and recalculate the cluster center C^t of Eq.(6).

$$c_j^t = \frac{\sum_{x_i \in C_j^{t-1}} h_i^t}{|C_j^{t-1}|} \quad (6)$$

Step4: Use the hidden representations of training samples as the input of Softmax classifier in order to train the classifier of Eq.(7).

$$P(l = j | h_i; \theta) = \frac{\exp^{h_i^T \theta_j}}{\sum_{k=1}^K \exp^{h_i^T \theta_k}} \quad (7)$$

end while

Step5: Use the optimized Clustering-WAE classification model to classify

$$c_j^t = \frac{\sum_{x_i \in C_j^{t-1}} h_i^t}{|C_j^{t-1}|} \quad (6)$$

Softmax Equation:

$$P(l = j | h_i; \theta) = \frac{\exp^{h_i^T \theta_j}}{\sum_{k=1}^K \exp^{h_i^T \theta_k}} \quad (7)$$

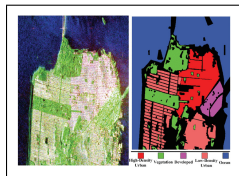


Figure: Pauli RGB and ground-truth image of San Francisco.

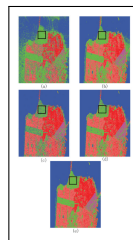


Figure: Classification results of different methods: K-means, Wishart, AE, WAE, and Clustering-WAE.

Table: Classification performances of San Francisco with different methods.

	<i>K-means</i>	<i>Wishart</i>	<i>AE</i>	<i>WAE</i>	<i>Clustering-WAE</i>
<i>High-density</i>	29.95	49.63	66.22	65.44	65.19
<i>Water</i>	75.76	97.13	99.90	99.83	99.73
<i>Vegetation</i>	38.82	92.62	68.47	83.57	80.32
<i>Developed</i>	55.97	57.84	57.18	65.99	68.39
<i>Low-density</i>	92.63	74.20	73.63	80.27	89.43
<i>OA</i>	66.50	83.33	84.08	87.44	88.53
<i>Kappa</i>	0.53	0.75	0.75	0.82	0.83