Examination of Kernel Based Noise Classifier with Cross Resolution Dataset and with Untrained Class

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Abstract*: Determining the effect of untrained classes in the kernel based noise classifier is the prime object of the paper. It further includes, studying the effect of studied classifier over different datasets. Distinct nine Kernel functions has been associated with conventional supervised Noise Classifier. Landsat8 and Formosat2 along with Resourcesat-1 data have been opted for the performance evaluation. Decrease in classification accuracy has been found, in presence of untrained classes. A subtle consistency has been in classification accuracy in case of cross resolution data sets, thus, showing the robustness of the algorithm.

Keywords: Kernel functions, Noise Clustering Classifier, Cross Resolution, and Untrained Classes.

I. INTRODUCTION

Substantial applications of Remote Sensing have directed to availability of enormous magnitude of imagery. Prolonging the quality of imagery also has multiplied, ensuing to requirement of vigorous framework for image processing and evaluation.

The extensive use of fuzzy logic [26] for classification leads into soft classifiers. Among the most prominent fuzzy classifiers, Fuzzy *c*-mean algorithm had shown successful results over estimation and assessment of sub-pixel based data, although it failed to handle noise [9, 20]. Various classification techniques were implemented and Noise Clustering found to be unsurpassed [6, 7].

Studies related to spatial contextual information in the classification process illustrates improvement in the classifiers robustness against noise when compared to spectral based algorithm[13].Isolated pixels irregularity can be handled classifying using contextual classifiers. MRF based contextual has proven to be reliable classification with improved accuracy [3, 24]. Contextual support to Noise classifier was proposed earlier to overcome sensitivity of noise and outliers on the classification result using S-MRF or DA-MRF models [10].

Previous studies show that hybridization of conventional fuzzy based related to kernels have been done using different techniques. The underlying concept is mapping the data to higher dimension to make it linearly separable [4,11]. Different studies have been made with kernels to improve the classification. Associating Gaussian and higher order polynomial with unsupervised Noise Clustering algorithm found to be relatively more resistant against noise [5]. Similar study for noise robustness was examined by replacing Euclidean norm with Gaussian Kernel in PCM [12, 18]. Local kernel as well as the global kernels were studied and incorporated to enhance the capability of FCM [2]. In the similar form, study of incorporating eight kernels with Fuzzy *c*-Means has shown improved accuracy [4].

In supervised classification, it is impossible to get sample for all classes present in the study area or some of the classes may not be considered for classification. As a result, some of the classes are left untrained during classification. Lately, the effect of untrained classes during classification was also analyzed, with kernel based FCM, stating the presence of untrained classes affects the membership value and decreases the correspondence between the estimated and the actual class composition [4]. Similarly, kernels with PCM have shown high resistivity to untrained classes [14]. In supervised classification, the untrained class generated by escaping the training of classifier for a particular class. The similar examination has been opted for KNC classification.

This paper is the extension of the previous work done related kernel based noise classifier, KNC, using nine-kernel function in supervised model [16, 17]. The objective of present paper is to assess the associativity of untrained class upon kernel based noise classifier. Secondly, the paper also covers the effect of classification upon distinct resolution dataset.

II. STUDY AREA AND DATASET DESCRIPTION

The area of study is Haridwar district in state of Uttarakhand, India. Area extends from 29°52’49” N to 29°54’2” N and 78°9’43” E to 86 78°11’25” E. The dataset used in classification are Landsat8 and Formosat2, with defined sensor details in Table 1 and Table 2.

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Table 1: Data Details of Landsat8[20]

Spectral Band	Wavelength (μm)	Resolution (m)
Band 1 - Coastal aerosol	0.43 - 0.45	30
Band 2 – Blue	0.45 - 0.51	30
Band 3 – Green	0.53 - 0.59	30
Band 4 – Red	0.64 - 0.67	30
Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
Band 6 – Short Wavelength Infrared 1	1.57 - 1.65	30
Band 7 –Short Wavelength Infrared 2	2.11 - 2.29	30
Band 8 - Panchromatic	0.50 - 0.68	15
Band 9 – Cirrus	1.36 - 1.38	30

Table 2: Data Details of Formosat2[21]

Spectral Band	Wavelength (μm)	Resolution (m)
Band 1 - Blue	0.45 - 0.52	8
Band 2 - Green	0.52 - 0.60	8
Band 3 - Red	0.63 - 0.69	8
Band 4 - Near Infrared (NIR)	0.76 - 0.90	8
Band 5 - Panchromatic	0.45 – 0.90	2

III. EMPLOYED KERNEL METHODS

Kernel methods direct to map the data to higher dimension to make it linearly separable [1, 19]. The generalized mathematical expression shown in Eq.(3.2), where (φ) denotes the mapping function that non-linearly maps the data to a higher dimensional feature space and the kernel function (K) feature map given in Eq.(3.1).

$$\Phi : R^{p} \rightarrow R^{q} \text{, where p<q} \tag{3.1}$$

$$K\left(\vec{x}, \vec{x_i}\right) = \phi(x)\phi(x_i) \tag{3.2}$$

Table 3 displays the kernel methods used with algorithm. These nine kernels have been categorized as: four local kernels, three global kernels, spectral kernel, and hypertangent kernel [14].

Table 3: List of Kernel Methods Employed[16,17].

Local Kernels	
Kernel Name	**Mathematical Formulae**
Radial Basis Function (RBF)	$K\left(\vec{x_i}, \vec{v_j}\right) = e^{\left(\frac{\left\|x_i^{a} - v_j^{b}\right\|^2}{2\sigma^2}\right)}$, where σ, a, b > 0
RBF kernel, defined by exponential function [4, 13]. σ determines the width of the kernel; a and b are the constants.	
KMOD- (Kernel with Moderate Decreasing)	$K\left(\vec{x_i}, \vec{v_j}\right) = e^{\left(\frac{\gamma}{\sigma^2 + \left\|x_i - v_j\right\|^2}\right)^{-1}}$, where $\sigma, \gamma > 0$
KMOD a distance based kernel function and shows better result in classifying closely related datasets[1].	
Gaussian	$K\left(\vec{x_i}, \vec{v_j}\right) = e^{\left(-\frac{\left\|x_i^{a} - v_j^{b}\right\|^2}{2\sigma^2}\right)}$, where $\sigma > 0$
The Gaussian kernel is a special case of radial basis function kernel[16].	
Inverse Multi-Quadratic (IMQ)	$K\left(\vec{x_i}, \vec{v_j}\right) = \frac{1}{\sqrt{\left(\left\|x_i - v_j\right\|^2 + c\right)}}$, where c > 0
Here the value of c was taken to be one.	
Global Kernels	
Linear kernel	$K\left(\vec{x_i}, \vec{v_j}\right) = x_i . v_j$
It is the simplest and is defined as the inner product of the input feature vectors.	
Polynomial	$K\left(\vec{x_i}, \vec{v_j}\right) = \left(x_i . v_j + c\right)^{P}$, where $c \geq 0$ (P=1to 4)
The polynomial kernel is a positive, where, P denotes the degree of the polynomial function and c is the constant.	
Sigmoid	$K\left(\vec{x_i}, \vec{v_j}\right) = \tanh\left(\alpha . x_i . v_j + c\right)$
Sigmoid kernel is a hyperbolic tangent function. The parameter α defines width of the kernel[15].	

Spectral Kernel	
$\alpha(x, v_i) = \arccos\left(\frac{(x . v_i)}{\|x\|\|v_i\|}\right)$	The spectral kernel works upon the concept of spectral signature concept and uses spectral angle to determine vector distance[15] .
Hypertangent Kernel	
$K(x, v_i) = 1 - \tanh\left(-\frac{\|x - v_i\|^2}{\sigma^2}\right)$	The hyper tangent kernel is a hyperbolic tangent function. The adjustable parameter σ defines the width of the kernel. It had seen that this kernel outperforms other kernels when applied to a large data set [18].

IV. CLASSIFICATION

Supervised Kernel Based Noise Clustering (KNC)

This classifier was derived by using kernel methods with Noise classifier (NC) [6,7,8]. The objective function derived implies the replacement of Euclidean distance with the prescribed kernel function $K(x_i, v_j)$

$$J_{KNC}(U,V) = \sum_{i=1}^{N}\sum_{j=1}^{C}\mu_{ij}^{m} K(x_i, v_j) + \sum_{i=1}^{N}\mu_{i,c+1}{}^{m}\delta \tag{4.1}$$

To measure the non-linearity among the classes on the basis of spatial features, contextual support has been provided using MRF models with KNC. The study results in the generation of hybrid classifier and results were found promising [18,19]. Table 4 denotes the mathematical representation of hybrid classifiers.

V. UNTRAINED CLASS AND CROSS RESOLUTION DATA SET DESCRIPTION

Untrained Class

In supervised classification to get samples of all classes present in defined area of study is unattainable. Certain classes may not be considered for classification and thus represented as untrained. Such classes confirm showing high membership values for spectrally different class and thus, results in decrease of the classification accuracy [4].

Cross-resolution Dataset

To study the effect of classifier over different resolution data sets, AWiFS (Advanced Wide Field Sensor), LISS-III (Linear Imaging Self Scanner) and LISS-IV images from the Resourcesat-1 (Indian Remote sensing Satellite-P6) have been used in the studied classifier. The specifications are illustrated in Table 5.

Table 5: Data Details of Resourcesat-1[22]

Specifications	LISS-IV	LISS-III	AWiFS
Spatial resolution (m)	5.8	23.5	56
Spectral Bands (microns)	0.52-0.59 0.62-0.68 0.77-0.86	0.52-0.59 0.62-0.68 0.77-0.86 1.55-1.70	0.52-0.59 0.62-0.68 0.77-0.86 1.55-1.70
Quantization (bits)	7	7	10

Table 4: Kernel based Contextual Noise Classifiers [14, 19]

Kernel based Contextual Model	
Smoothness Prior – KNC-S-MRF	$U\left(\frac{u_{ij}}{d}\right) = (1-\lambda)\left[\sum_{i=1}^{N}\sum_{j=1}^{C}(u_{ij})^{m} K\left(\vec{x}_i, \vec{v}_j\right) + \sum_{i=1}^{N}(u_{i,C+1})^{m}\delta\right] + \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{C}\sum_{j'\in N_j}\beta(u_{ij}-u_{ij'})^{2}\right]$
Discontinuity Adaptive Prior (Type 1) - KNC-DA1-MRF	$U\left(\frac{u_{ij}}{d}\right) = (1-\lambda)\left[\sum_{i=1}^{N}\sum_{j=1}^{C}(u_{ij})^{m} K\left(\vec{x}_i, \vec{v}_j\right) + \sum_{i=1}^{N}(u_{i,C+1})^{m}\delta\right] + \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{C}\sum_{j'\in N_j}(-\gamma e)^{-\frac{\eta^2}{\gamma}}\right]$
Discontinuity Adaptive Prior (Type 2) – KNC-DA2-MRF	$U\left(\frac{u_{ij}}{d}\right) = (1-\lambda)\left[\sum_{i=1}^{N}\sum_{j=1}^{C}(u_{ij})^{m} K\left(\vec{x}_i, \vec{v}_j\right) + \sum_{i=1}^{N}(u_{i,C+1})^{m}\delta\right] + \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{C}\sum_{j'\in N_j}\frac{-\gamma}{1+\frac{\eta^2}{\gamma}}\right]$
Discontinuity Adaptive Prior (Type 3) - KNC-DA3-MRF	$U\left(\frac{u_{ij}}{d}\right) = (1-\lambda)\left[\sum_{i=1}^{N}\sum_{j=1}^{C}(u_{ij})^{m} K\left(\vec{x}_i, \vec{v}_j\right) + \sum_{i=1}^{N}(u_{i,C+1})^{m}\delta\right] + \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{C}\sum_{j'\in N_j}\left(\gamma\ln\left(1+\frac{\eta^2}{\gamma}\right)\right)\right]$
Discontinuity Adaptive Prior (Type 4) - KNC-DA4-MRF	$U\left(\frac{u_{ij}}{d}\right) = (1-\lambda)\left[\sum_{i=1}^{N}\sum_{j=1}^{C}(u_{ij})^{m} K\left(\vec{x}_i, \vec{v}_j\right) + \sum_{i=1}^{N}(u_{i,C+1})^{m}\delta\right] + \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{C}\sum_{j'\in N_j}\left(\gamma\lvert\eta\rvert-\gamma^{2}\ln\left(1+\frac{\eta^2}{\gamma}\right)\right)\right]$

VI. RESULTS

Untrained class outputs have been computed by omitting to train the feature data of the particular class, here in this study water class was considered as untrained class. The process includes discarding a specific class while classifier training to quantify the robustness of kernel based noise classifier as well as its execution. The classifiers taken under consideration are KNC, KNC-SMRF, KNC-DA1MRF, KNC-DA2MRF, KNC-DA3MRF, and KNC-DA4MRF. Illustrations of Kernel wise overall accuracy is in Table 6, among them Hypertangent Kernel has shown more robustness in comparison to other kernels. On the other side, Polynomial kernels have shown zero effect upon classifier. Similarly, Table 7 displays the kernel wise overall accuracy when contextual support has been added using MRF models with KNC. Table 4 demonstrates the overall accuracy of Gaussian, Sigmoid and Hypertangent kernel.

Table 6: Accuracy assessment results for trained and untrained class using KNC.

Kernels	Untrained	Trained
Linear	8.23%	11.35%
Hypertangent	81.62%	82.19%
Gaussian	69.70%	82.39%
IMQ	70.12%	82.64%
Radial	69.75%	81.60%
Polynomial(Degree=1)	7.23%	11.16%
Polynomial(Degree=2)	0.00%	0.00%
Polynomial(Degree=3)	0.00%	0.00%
Polynomial(Degree=4)	0.00%	0.00%
KMOD	69.12%	82.15%
Sigmoid	66.14%	79.25%
Spectral	85.33%	90.66%

Table 7: Accuracy assessment results for trained and untrained class using KNC-SMRF, KNC-DA1MRF, KNC-DA2MRF, KNC-DA3MRF, and KNC-DA4MRF.

Contextual Models	UNTRAINED				TRAINED				
(Classifier)	S-MRF	DA1-MRF	DA2-MRF	DA3-MRF	DA4-MRF	S-MRF	DA1-MRF	DA2-MRF	DA3-MRF	DA4-MRF
Gaussian Kernel	68.54%	68.10%	67.89%	61.46%	62.91%	76.63%	81.09%	70.38%	59.42%	52.59%
Sigmoid	63.85%	65.12%	60.22%	55.89%	61.44%	73.51%	75.38%	66.30%	51.04%	37.97%
Hypertangent	67.00%	67.09%	65.00%	65.20%	48.98%	75.95%	78.75%	70.09%	60.91%	50.85%

Effect of studied classifiers on across resolution data sets

To analyze the impact, FERM (Fuzzy Error Matrix) based accuracy assessment results were computed [3,13]. The output images set off from finer resolution LISS-IV dataset as reference corresponding to AWIFS and LISS-III classification results. Table 8 and Table 9 show the overall accuracy across the different datasets using optimized range of fuzzifier m between 2.7 to 5.0. The kernels taken into consideration KMOD and Spectral are best performing kernels in KNC. In similar pattern, for KNC with MRF Models Gaussian, Hypertangent and Sigmoid have been the outperformers [20]. The overall assessment shows minimal reflectance in performance with change in datasets, thus, retaining the robustness of the classifiers.

Table 8: Accuracy assessment results for KNC upon distinct datasets

m (Fuzzy parameter)	AWIFS against LISS-IV (Resourcesat-1)		AWIFS LISS-III (Resourcesat-1)		LISS-III against LISS-IV (Resourcesat-1)		Landsat8 against Formosat2	
	KMOD	Spectral	KMOD	Spectral	KMOD	Spectral	KMOD	Spectral
2.7	86.85%	88.02%	91.41%	92.85%	87.37%	90.39%	80.02%	88.79%
3	89.26%	89.87%	92.79%	93.82%	89.34%	91.99%	82.15%	90.66%
3.5	90.26%	92.20%	93.93%	95.42%	91.14%	93.62%	85.14%	92.77%
4	91.52%	93.38%	95.05%	96.14%	92.71%	94.54%	87.09%	93.88%
4.5	92.96%	94.25%	95.56%	96.53%	93.69%	95.45%	88.54%	94.65%
5	94.26%	95.14%	96.21%	97.17%	94.44%	95.99%	90.39%	95.55%

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Table 9: Accuracy assessment results for KNC-SMRF, KNC-DA1MRF, KNC-DA2MRF, KNC-DA3MRF, and KNC-DA4MRF upon distinct datasets

Contextual Classifier	AWIFS against LISS-IV (Resourcesat-1)			AWIFS LISS-III (Resourcesat-1)			LISS-III against LISS-IV (Resourcesat-1)			Landsat8 against Formosat2		
	Gaussian	Hypertagent	Sigmoid	Gaussian	Hypertagent	Sigmoid	Gaussian	Hypertagent	Sigmoid	Gaussian	Hypertagent	Sigmoid
KNC-SA-MRF	84.63%	84.07%	80.10%	89.88%	94.29%	87.26%	88.21%	85.31%	84.09%	76.63%	75.95%	73.51%
KNC-DA1-MRF	87.22%	86.57%	82.39%	91.18%	90.54%	87.71%	87.18%	87.28%	83.92%	81.09%	78.75%	75.38%
KNC-DA2-MRF	80.53%	81.10%	72.82%	77.37%	88.03%	87.12%	84.38%	82.81%	78.61%	70.38%	70.09%	66.30%
KNC-DA3-MRF	69.66%	68.97%	54.78%	78.84%	79.46%	65.23%	74.21%	73.95%	65.77%	59.42%	60.91%	51.04%
KNC-DA4-MRF	53.71%	55.61%	46.35%	64.14%	69.09%	58.28%	68.04%	66.90%	57.21%	52.59%	50.85%	37.97%

VII. CONCLUSION

The paper focuses to assess the strength of classification algorithms KNC, KNC-SMRF, KNC-DA1MRF, KNC-DA2MRF, KNC-DA3MRF, and KNC-DA4MRF. Incorporation of untrained class and the effect of using different datasets has been the prime thrust of study. Results presented shows slight decrease in overall accuracy of the kernel-based classifiers, and Hypertangent Kernel has shown the minimal transform in accuracy. For cross resolution data AWIFS, LISS-III and LISS-IV images from the Resourcesat-1 (Indian Remote Sensing Satellite-P6) have been used in the studied classifier and have resulted in with minor change in overall accuracy. Thus, concluding that supplanting another dataset with studied classifiers have not influenced the robustness of kernel based noise classifier.

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