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Assimilation of Standard Regularizer Contextual Model and Composite Kernel with Fuzzy-based Noise Classifier

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Abstract: The paper assay the effect of assimilating smoothness prior contextual model and composite kernel function with fuzzy based noise classifier using remote sensing data. The concept of the composite kernel has been taken by fusing two kernels together to improve the classification accuracy. Gaussian and Sigmoid kernel functions have opted for kernel composition. As a contextual model, Markov Random Field (MRF) Standard regularization model (smoothness prior) has been studied with the composite kernel-based Noise Classifier. Comparative analysis of new classifier with the conventional construes increase in overall accuracy.
Keywords: Kernel functions; Composite kernel; Markov Random Field (MRF) model; Regularization model.

1. Introduction

Sustaining the worth of the remotely sensed data has become a matter of contest, thus, necessitating vigorous context of processing and valuation of these data. Established classification practices use to designate every pixel to a definite group ensuing into hard segregation [1], coarse spatial resolution, and results in association of an individual pixel to more than one land-cover type, known as a mixed pixel [2] and ignorance of it resulted in a reduction in classification accuracy.

Among the most prominent fuzzy classifiers, conceptualized from fuzzy logic, Fuzzy c-mean (FCM), had done well sub-pixel classification [3, 4], although it failed to handle noise. Consideration of noise handling was looked upon in various fuzzy based classifiers and among them Noise clustering was found superlative [5, 6].

Contribution of spatial contextual information in the fuzzy based classification lead to improvement in the classifiers robustness against noise [3, 7]. Contextual model like, MRF (Markov Random Field) had been used for classification, resulting in improved accuracy [8, 9]. MRF model with FCM was introduced as a Robust Fuzzy *c*-Means (RFCM) algorithm, while performing image segmentation of Magnetic Resonance Images of brain [10]. Progress in classification has been seen through combining the advantages of Adaptive classifier and Bayesian Contextual classifier using MRF modeling [11]. Providing contextual support to Noise classifier had also been discussed with the aim to surmount understanding of noise and outliers on the classified output using MRF models. Study over integrating the contextual information by support vector machines classifier using MRF model for classification enhancement also been prepared [12].

Investigation and review over kernel methods states the gain of scheduling the feature data to a high dimension space where it results to be linearly separable [13]. Kernels with fuzzy based classification have shown successful classification outcomes. The composite kernel concept is introduced to merge the efficiency of two different kernel function [14]. The composite kernel function leads to progress in classification accuracy as compared to primitive single kernel and also provides the flexibility to adjust between the influences of the kernels by including weight factor [15]. Some prominent techniques for combining kernels are stacked approach, direct summation kernel, weighted summation kernel and cross-information kernel [16, 17]. In this paper the kernel composition has been devised with weighted summation kernel method. Association of Kernels with fuzzy based classifier has shown effectual yield than the typical ones.

The objective is to illustrate the upshot of combining the positives of spectral classification with the contextual spatial information. Supervised Noise Clustering has been opted as the base classifier, with distance function as GaussianSigmoid composite kernel, termed as, GaussianSigmoid-KNC. For contextual support Markov Random Field (MRF), Standard regularization model has been incorporated with KNC for edge preservation and abbreviated as GaussianSigmoid-KNC-S-MRF. Fuzzy error matrix (FERM) and Sub-pixel Confusion Matrix (SCM) has been applied as image to image accuracy assessment metric.

2. Study area and dataset used

Landsat-8 and Formosat-2 satellites have been used for data acquisition. The area under study is situated in Haridwar district in the state of Uttarakhand, India. Water, Wheat, Forest, Riverine Sand, and Fallow Land, these five land cover classes have been ascertained for classification. The area extends from 29°52’49” N to 29°54’2” N and 78°9’43” E to 78°11’25” E. Landsat-8 is 8 bands sensor with spatial resolution of 30m (meters) on the other hand Formosat-2 is fine resolution 4 bands sensor with spatial resolution of 8m (meters) [18, 19].

3. Composite kernel-based noise classification with MRF models

The novelty of the present work is to incorporate composite kernel method with supervised Noise Clustering, and further integrate it contextual Smoothness Prior model with it.

3.1 Composite kernel employed

Kernel functions enables to work upon higher dimension without undergoing into that space, by simply computing the inner product (dot product) between all pair of data in feature space (φ), this technique is known as *kernel trick.* The kernel intends to detect a linearly separating hyperplane that separates the classes in higher dimension feature space, as non-linear separable classes seem to be linear in higher dimension. Equation (1), illustrates the mathematical representation of kernel function (K), that computes the inner product of vectors $\boldsymbol{x}$ and $\boldsymbol{y}$ in higher dimension space unambiguously.

$$K\left(\vec{x},\vec{y}\right) = \varphi(x)\cdot\varphi(y) \tag{1}$$

The present study has followed weighted kernel summation approach as defined in equation (2) for input feature vector x and$y$. The weight factor $\lambda_{composite}$ varies between (0, 1) and is optimized to get the best mixing between two kernels. Here K_a and K_b are two different kernel functions that are used to form the composite kernel K [16,17]. Kernel methods used are Gaussian Kernel and Sigmoid Kernel.

$$K_{composite}\left(\vec{x},\vec{y}\right) = \lambda_{composite}K_a(x,y) + \left(1-\lambda_{composite}\right)K_b(x,y) \tag{2}$$

3.1.1 Gaussian kernel

The kernels based on distance function are local kernels [20, 21]. Gaussian kernel is a form of local kernel**,** where $\boldsymbol{x}$ is the feature vector in the image and $\boldsymbol{y}$ is the mean vector of the class.

$$K\left(\vec{x},\vec{y}\right) = e^{\left(-\frac{\left\|x^a-y^b\right\|^2}{2\sigma^2}\right)} \tag{3}$$

where $\sigma > 0$.

3.1.2 Sigmoid kernel

Sigmoid kernel is a hyperbolic tangent function and belongs to the class of global kernel [21]. The scaling parameter is α for the kernel functions that defines width of the kernel [20].

$$K\left(\vec{x},\vec{y}\right) = \tanh(\alpha\cdot x\cdot y + c) \tag{4}$$

3.2 Markov Random Field (MRF)

Contextual information represents the relationship of an entity with neighbourhood and from image pixel perspective; in other words, it is related to neighbouring pixel information. Previous studies have concluded that apt utilization of context outcomes to upgraded classification [8, 11, 22]. Study over MRF Models have been accomplished and propagated stating the relevance of neighbourhood pixel with local interaction [23].

3.3 Prior energy

A prior to milieu with an image defines the aforementioned information and to represent prior energy, Analytical regularizers are applied. The regular form of a regularizer is mentioned in equation (5) [24]. This prior energy function expressed as $U(f)$ and provides the former details of image of n^{th} order regularizer. Assumption of smoothness in context to image classification is implemented to replicate the prior information. Smoothness

Prior has been functionalised to model such concept. Also potential function, expressed as, $g\left(f^{(n)}(x)\right)$ which is reliant upon the irregularity associated in$f^{(n-1)}(x)$, N is the highest order considered and λ_n is the weighting factor, greater than or equal to 0 [23].

$$U(f) = \sum_{n=1}^{N} U_n(f) = \sum_{n=1}^{N} \lambda_n \int_n^b g\left(f^{(n)}(x)\right) dx \tag{5}$$

3.4 Smoothness prior (standard regularizer)

A digital image comprises of DN (Digital Number) values of the pixels that are unswerving by nature. Therefore, smoothness is common notion with context to prior usage. This assumption of smoothness can be denoted mathematically by a prior probability as energy and to study the model, analytic regularization model can be utilized [24, 25]. Present work has represented *standard regularizer* as smoothness prior. Standard regularizers are used for smoothness prior and are characterized as quadratic function, as, given by equation (5)

$$g\left(f^{(n)}(x)\right) = g(\eta) = \eta^2 \tag{6}$$

3.5 Composite-kernel based noise clustering without entropy classification (Composite-K.N.C)

The general tendency of composite kernel is to fuse the spectral and textual details present in the input image to the classified outputs, resulting with increase in classification accuracy. The similar concept has been adapted in the present work, thus, deriving, the Composite-K.N.C classifier by adding in composite kernel method with Noise clustering without entropy classifier. The objective function of the base classifier used, i.e., Noise Classifier in fuzzy mode [5, 22, 25] has been expressed in equation (7)

$$J_{NC}(U,V) = \sum_{i=1}^{N} \sum_{j=1}^{c} (\mu_{ij})^m D\left(\vec{x_i}, \vec{v_j}\right) + \sum_1^N (\mu_{i,c+1})^m \delta \tag{7}$$

where $U = N \times c + 1$matrix, V= ($v_{1\ldots}$ v_C), c denotes number of classes, N represents total number of pixels in the image, m is the fuzzification factor and is normally positive, μ_{ij} represent the membership value of i^{th} pixel in the j^{th} class, $\mu_{i,c+1}$ represents the membership values of the noise class, v_j is the mean value (cluster center) of the j^{th} class, x_i is the vector value of the i^{th} pixel, D is the Euclidean distance between $\vec{x_i}$and $\vec{v_j}$and δ is a positive constant called the Noise distance.

Derivation of Composite-K.N.C has been done by substituting distance function D with $K(x_i, v_j)$ namely the composite kernel function mentioned in equation (2). The consequential mathematical design has been indicated with equation (8) and equation (9).

$$D\left(\vec{x_k}, \vec{v_i}\right) = K_{composite}(x_k, v_i) \tag{8}$$

$$J_{Composite-KNC}(U,V) = \sum_{i=1}^{N} \sum_{j=1}^{c} \mu_{ij}{}^m K_{composite}(x_i, v_j) + \sum_{i=1}^{N} \mu_{i,c+1}{}^m \delta \tag{9}$$

Furthermore, Composite-K.N.C has been modelled with the smoothness prior. Thus, the hybrid classifier obtained in equation (10) will be expressed as Composite-K.N.C-S-MRF. $U(u_{ij}/d)$, denotes the posterior probability, β is the weight factor associated with a pixel's neighbors and Nj represents the neighborhood window around pixel i.

$$U\left(\frac{u_{ij}}{d}\right) = (1-\lambda)\left[\sum_{i=1}^{N}\sum_{j=1}^{c}(u_{ij})^m K_{composite}\left(\vec{x_i}, \vec{v_j}\right) + \sum_{i=1}^{N}(u_{i,c+1})^m \delta\right] + \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{C}\sum_{j' \in N_j}\beta\left(u_{ij} - u_{ij'}\right)^2\right] \tag{10}$$

3.6 Mean-variance method

Measuring the degree of fuzziness present in the edges this technique is significantly opted. In other words, to monitor the effect of Smoothness prior model in preserving the edge is significant. Digital image perspective, an edge arises when sudden changes occur in grey level values or DN values. Mathematically, it has been proven where the difference between the average values contained by the specific regions indicates the steepness of the edge [26].

Mean-Variance method conceptualizes the membership value of the pixel in the fractional image is elevated if the pixel belongs to a known class (Class A) and to the unidentified, it is small (Non-Class A), elaborated in Fig

1. Subsequently, the unvarying area (Class A) results to high mean of the membership value and low variance in a fractional image, leading to edge preservation. This concept has been preferred in Composite-K.N.C-S-MRF classifier for both edge verification and contextual parameter optimization.

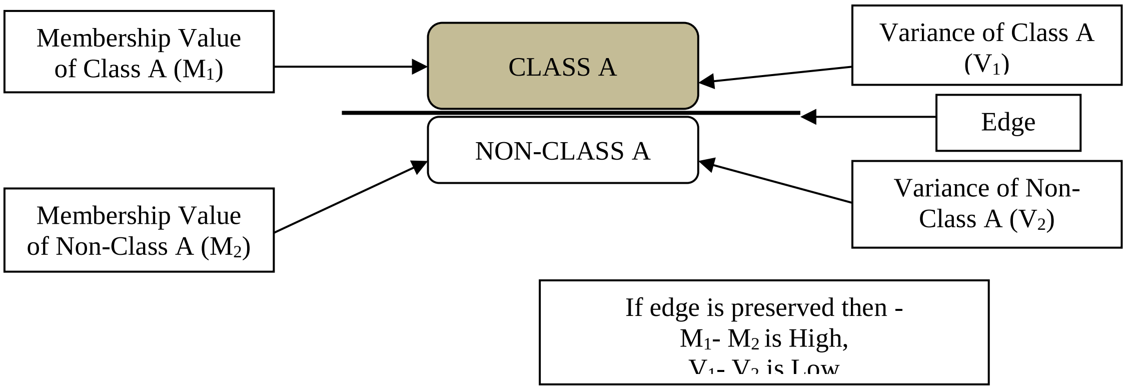


Fig. 1. Method to verify edge preservation

4. Accuracy assessment techniques

To assess the discussed soft classifier, simulated image method and FERM (Fuzzy error matrix) has been taken for computing and assessing the accuracy of Composite-KNC-S-MRF model. Accuracy assessment of sub-pixel classified output has been done with Java based tool [27].

4.1 Simulated image method

This approach has been used to estimate the performance of fuzzy based classifier and also to spot classifier conduct with the mixed pixels [16, 17, 20]. Class wise sample data or generation of this image has been prepared from mean vector of the classes via distance measure. The image has been partitioned into three variations – Pure Pixel composition, Mixed Pixel Composition (50:50) between two classes, and Mixed Pixel Composition (30:30:40) among three classes [20]. Undergoing supervised classification, the pixel values will be examined with the aimed membership value of 0.50, 0.40 and 0.30 as anticipated pixel with 50%, 40% and 30% fitting to the class respectively. Fig 2 explains the structure of simulated image on the basis of class distribution.

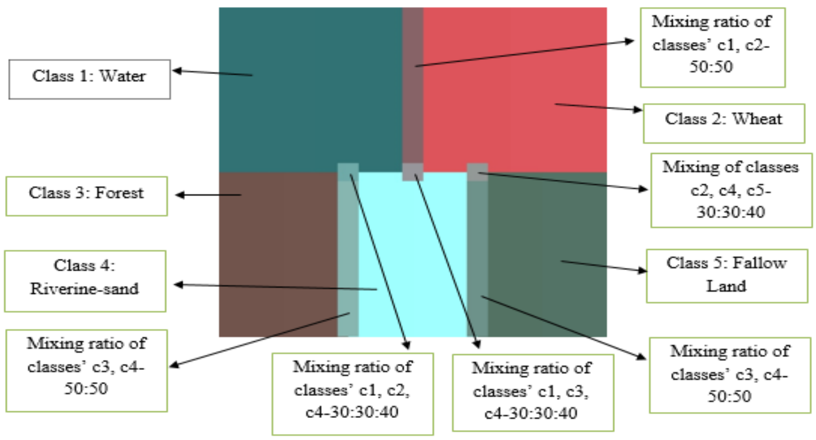


Fig. 2. Class Distribution of Formosat2 Simulated Image [20].

4.2 Fuzzy Error Matrix (FERM)

It is a matrix representation where rows (R_N) represent the number of sample components of classified data *m* and column denotes the number of sample elements belonging to reference data class *n*. Here these sample values belongs to fuzzy set membership values varying between [0, 1]. The values of fuzzy error matrix (***M***) is computed as shown in equation (11) [20,28], where, x is the overall sampled data set. μ_{Cm} and μ_{Rn} are the membership value for the classified and referenced data. The "min" operator is the fuzzy set operator, holding the minimum membership value between the classified and referenced data set for a class.

$$\mathrm{M}(m,n) = \sum_{x \in X} \min\left(\mu_{C_m}(x), \mu_{R_n}(x)\right) \tag{11}$$

4.3 Sub-pixel Confusion Matrix (SCM)

Difficulty in determination of overlap between the classes results in sub-pixel area allocation problem [29]. Alternative solution to it is confusion intervals. Sub-pixel Confusion Matrix (SCM) is also a modification of traditional error matrix and contains confusion intervals in the form of mean value plus-minus the maximum error [30]. Assessing the pixel class relationship various operators are associated with it, and they referred as MIN, PRODS, LEAST, MIN-PROD, MIN-MIN, and MIN-LEAST.

5. Result and analysis

5.1 Parameter estimation

The objective function of Composite- KNC S-MRF classifiers implicates certain parameters to situate before the optimization, thus, implementation of this hybrid classifier has been done in Java. Base classifier estimation has been done by a series of classification upon simulated image, using GaussianSigmoid kernel for every combination of m (fuzzy component) between 1.1 to 5.0 with interval of 0.1 , fixed value of the resolution parameter, δ, has been considered, and the estimation of composite kernel weight component $\lambda_{composite}$, has been done within the range of (0,1). The parameter selection of $\lambda_{composite}$ based on the implementation of accuracy assessment method FERM and mean-variance method. Contextual parameters have been estimated through simulated annealing (Bertsimas and Tsitsiklis, 1993) and mean variance method, initial T_0 has been set to 3 where optimized final temperature has been taken to be 0.90, λ has been defined in the range between 0 and 1, and range of β to be 1 to 100.

5.1.1 Base classifier parameter estimation

A series of GaussianSigmoid kernel based classification has been conducted upon simulated image with every combination of defined m with fixed δ. Optimized value of δ is 10^4 and that of m found to stabilize in the range between 2.5 to 4.0, the overall accuracy of the composite kernel weight constant,$\lambda_{composite}$, tends to set its value at 0.2 across m, as shown in Table 1, implying that, 0.2 proportion of Gaussian Kernel when added with 0.8 proportion of Sigmoid Kernel, accuracy tends to increase. For brief demonstration, Table 2 and Table 3, displays the membership values for both pure and mixed pixel variations of water and wheat class for both classifiers, with optimized value of base classifier, m is 2.7 and δ is 10^4, similar behaviour have been recorded for remaining classes.

Table 1. Overall Accuracy of GaussianSigmoid-K.N.C-S-MRF against weight factor ($\lambda_{composite}$)

m (Fuzzy Component)	$\lambda_{Composite}$								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
2.7	76.17%	75.96%	76.75%	76.37%	75.77%	75.38%	76.74%	77.28%	75.72%
3.0	78.15%	80.28%	79.47%	80.14%	79.89%	79.42%	79.09%	78.76%	79.09%
3.5	82.85%	82.41%	82.20%	83.41%	82.73%	82.22%	82.76%	81.93%	82.90%
4.0	85.87%	86.09%	85.67%	85.09%	85.83%	85.28%	85.66%	84.69%	84.99%
4.5	87.76%	87.64%	87.20%	87.22%	87.37%	86.91%	87.47%	86.85%	88.21%
5.0	89.63%	88.96%	88.86%	89.04%	88.35%	88.74%	89.06%	89.32%	88.99%

Table 2. Membership Value of Water Class (Pure and Mixed pixel variations of GaussianSigmoid-K.N.C-S-MRF, Noise Clustering-S-MRF)

Classifier	GaussianSigmoid-KNC-S-MRF (Weight Factor: $\lambda_{Composite}$)									Noise Classifier (NC) with Euclidean Distance
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	
Pure Pixel Composition	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.96
Mixed Pixel Composition(50:50)	0.14	0.14	0.14	0.14	0.15	0.15	0.15	0.15	0.15	0.14
Mixed Pixel Composition (30:30:40)	0.21	0.23	0.24	0.24	0.24	0.25	0.25	0.25	0.25	0.20

Table 3. Membership Value of Wheat Class (Pure and Mixed pixel variations of GaussianSigmoid-K.N.C-S-MRF, Noise Clustering-S-MRF)

Classifier	GaussianSigmoid-KNC-S-MRF (Weight Factor: $\lambda_{Composite}$)									Noise Classifier (NC) with Euclidean Distance
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	
Pure Pixel Composition	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Mixed Pixel Composition(50:50)	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.14
Mixed Pixel Composition (30:30:40)	0.17	0.18	0.19	0.18	0.16	0.19	0.19	0.20	0.20	0.20

5.1.2 Contextual parameter estimation

GaussianSigmoid-KNC-S-MRF classification involves contextual parameters, the weight factor that regulates the spatial and spectral module (λ) and neighborhood weight (β) . Estimation has been done upon the fractional images of GaussianSigmoid – K.N.C-S-MRF classification for Landsat8. Grey level pixel values derived from optimal range of hybrid parameters in case of K.N.C-S-MRF found to be λ lying between 0.7 to 0.9, β=7 to 20.These values has been tested under the mean-variance method for edge preservation. Table 4 displays the class wise estimates of GaussianSigmoid-K.N.C-S-MRF classification for λ=0.8, β=20, across every value of composite kernel weight constant $\lambda_{Composite}$.

Table 4. GaussianSigmoid –KNC-S-MRF estimation over Edge Verification for Landsat8 data

Gaussian Sigmoid-KNC-S-MRF	$\lambda_{Composite}$ =0.1		$\lambda_{Composite}$ =0.2		$\lambda_{Composite}$ =0.3		$\lambda_{Composite}$ =0.4		$\lambda_{Composite}$ =0.5		$\lambda_{Composite}$ =0.6		$\lambda_{Composite}$ =0.7		$\lambda_{Composite}$ =0.8		$\lambda_{Composite}$ =0.9	
	MD	VD	MD	VD	MD	VD	MD	VD	MD	VD	MD	VD	MD	VD	MD	VD	MD	VD
Water	178	172	178	125	178	153	177	146	178	141	177	141	176	137	177	138	177	130
Wheat	165	156	163	132	162	148	162	143	161	137	160	138	160	137	159	135	159	135
Forest	182	72	181	60	183	70	183	71	182	68	182	65	182	62	182	63	182	69
Riverine Sand	196	40	195	67	194	94	193	95	193	89	193	92	193	92	192	100	193	100
Fallow Land	162	139	162	116	161	165	160	170	160	165	160	186	160	182	159	191	159	187

5.2 Accuracy assessment

Studied hybrid classification has been applied upon Landsat8 and Formosat2 image using optimized values, resulting to generation of fractional images. Fractional outputs in Table 5 prove that GaussianSigmoid-K.N.C-S-MRF classification has shown better results than supervised Noise Classifier with Euclidean distance. FERM and SCM based accuracy metrics has been applied upon the outputs of Landsat8 and output of Formosat2 as reference map for GaussianSigmoid-K.N.C-S-MRF and NC (Euclidean)-S-MRF model. Table 6 shows the SCM based, user accuracy, producer accuracy and overall accuracy computed at m=5.0, $\lambda_{Composite}$ =0.2, with overall accuracy of 88.96% that is much higher than that of conventional classifier mentioned in Table 7.

6. Conclusion

The paper bestows the integration of GaussianSigmoid composite kernel function with Noise classifier with contextual information using Smoothness Prior-MRF model, results into developing a new classifier, characterized as GaussianSigmoid-K.N.C-S-MRF. The effect of this hybridization has been noted by increase in overall classification accuracy proving to control the presence of non-linearity among the classes.

Table 5. Fractional images obtained from GaussianSigmoid-K.N.C S-MRF and NC S-MRF classifiers on Formosat 2 and Landsat8 against the optimal parameters.

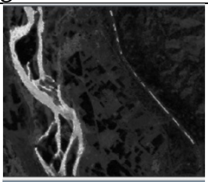
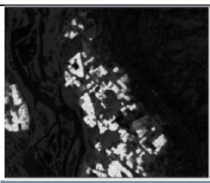
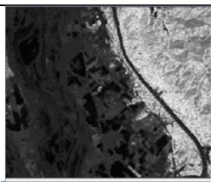
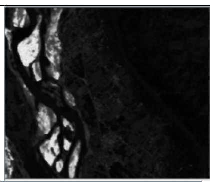
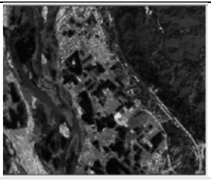
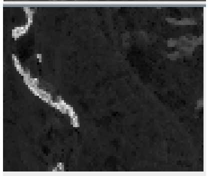
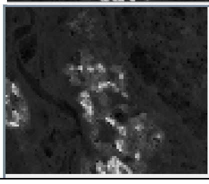
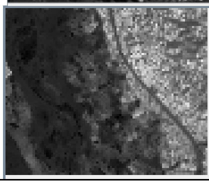
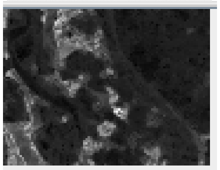
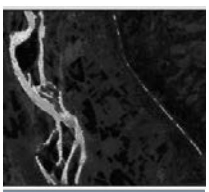
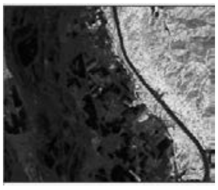
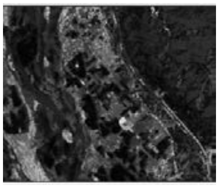
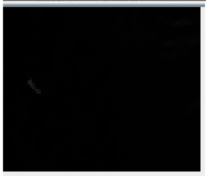
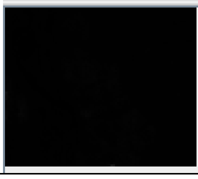
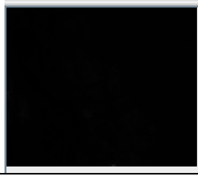
Classifier	Water	Wheat	Forest	Riverine Sand	Fallow
GaussianSigmoid-K.N.C-S-MRF					
Formosat2					
Landsat8					
NC-S-MRF					
Formosat2					
Landsat8					

Table 6. SCM based accuracy assessment for classified result of Landsat-8 dataset using GaussianSigmoid-K.N.C-S-MRF

Class-wise Accuracy		**SCM Percentage**
Water	User Accuracy	97.52 %+-1.85%
	Producer Accuracy	91.78%+-6.55%
Wheat	User Accuracy	85.41 %+- 9.72%
	Producer Accuracy	94.99 %+- 2.36%
Forest	User Accuracy	96.26%+-2.18%
	Producer Accuracy	91.50%+-4.72%
Riverine Sand	User Accuracy	89.06%+-8.56%
	Producer Accuracy	97.70%+-1.52%
Fallow Land	User Accuracy	96.25%+-2.16%
	Producer Accuracy	91.69%+-7.25%
Overall Accuracy		93.08%+-4.82%

Table 7. FERM based accuracy assessment for classified result of Landsat-8 dataset using GaussianSigmoid-K.N.C-S-MRF and NC-S-MRF

***m*(Fuzzy Component)**	GaussianSigmoid-KNC-S-MRF	NC-S-MRF
2.7	75.96%	4.00%
3.0	80.28%	8.71%
3.5	82.41%	18.23%
4.0	86.09%	28.79%
4.5	87.64%	37.66%
5.0	88.96%	45.72%

7. References

[1] Zhang J, Foody GM. A fuzzy classification of sub-urban land cover from remotely sensed imagery. International journal of remote sensing. 1998;19(14):2721-2738.

[2] Foody GM. Relating the land-cover composition of mixed pixels to artificial neural network classification output. Photogrammetric engineering and remote sensing. 1996;62(5):491-498.

[3] Foody GM. Estimation of sub-pixel land cover composition in the presence of untrained classes. Computers & Geosciences. 2000;26(4):469-478.

[4] Fisher PF, Pathirana S. The evaluation of fuzzy membership of land cover classes in the suburban zone. Remote Sensing of Environment. 1990;34(2):121-132.

[5] Dave RN. Characterization and detection of noise in clustering. Pattern Recognition Letters. 1991;12(11):657-664.

[6] Dave RN. Robust fuzzy clustering algorithms. In: Second IEEE International Conference on Fuzzy Systems ;1993. p. 1281-1286.

[7] Krishnapuram R, Keller JM. The possibilistic c-means algorithm: insights and recommendations. IEEE transactions on Fuzzy Systems. 1996;4(3):385-393.

[8] Solberg AH, Taxt T, Jain AK. A Markov random field model for classification of multisource satellite imagery. IEEE transactions on geoscience and remote sensing. 1996;34(1):100-113.

[9] Binaghi E, Madella P, Montesano MG, Rampini A. Fuzzy contextual classification of multisource remote sensing images. IEEE transactions on geoscience and remote sensing. 1997;35(2):326-340.

[10] Pham DL. Spatial models for fuzzy clustering. Computer vision and image understanding. 2001;84(2):285-297.

[11] Jackson Q, Landgrebe DA. Adaptive Bayesian contextual classification based on Markov random fields. IEEE Transactions on Geoscience and Remote Sensing. 2002;40(11):2454-2463.

[12] Moser G, Serpico SB. Contextual remote-sensing image classification by support vector machines and Markov random fields. In: 2010 IEEE International on Geoscience and Remote Sensing Symposium (IGARSS); 2010. p.3728-3731.

[13] Awan AM, Sap MN. Clustering spatial data using a kernel-based algorithm. In: Proceedings of the Postgraduate Annual Research Seminar 2005. p. 306-310.

[14] Kandpal N. Non-Linear Separation of classes using a Kernel based Possibilistic c -Means. [MSc. Thesis]. ITC, University of Twente,The Netherlands; 2016.

[15] Camps-Valls G, Gomez-Chova L, Muñoz-Marí J, Vila-Francés J, Calpe-Maravilla J. Composite kernels for hyperspectral image classification. IEEE geoscience and remote sensing letters. 2006;3(1):93-97.

[16] SenGupta I, Kumar A, Dwivedi RK. Study of SigmoidSpectral Composite Kernel based noise classifier with entropy in handling non linear separation of classes. In: 2018 5th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON); 2018. p. 1-6.

[17] SenGupta I, Kumar A, Dwivedi RK. Assessment of Spectral-KMOD Composite Kernel-Based Supervised Noise Clustering Approach in Handling Nonlinear Separation of Classes. In: Ambient Communications and Computer Systems. Springer, Singapore; 2019. p. 449-459.

[18] Formosat2Specification. https://earth.esa.int/web/eoportal/satellite-missions/f/formosat-2.

[19] Landsat 8 Specifications. https://landsat.usgs.gov/landsat-8.

[20] SenGupta I, Kumar A, Dwivedi RK. Performance Evaluation of Kernel-Based Supervised Noise Clustering Approach. Journal of the Indian Society of Remote Sensing. 2019;47(2):317-330.

[21] Lin HT, Lin CJ. A study on sigmoid kernels for SVM and the training of non-PSD kernels by SMO-type methods. submitted to Neural Computation. 2003;3:1-32.

[22] Harikumar A. The effects of discontinuity adaptive MRF models on the Noise classifier. [MSc. Thesis]. ITC, University of Twente, The Netherlands;2014.

[23] Singha M. Study the effect of discontinuity adaptive MRF models in fuzzy based classifier. [MSc. Thesis]. ITC, University of Twente, The Netherlands;2013.

[24] Li SZ. Markov random field modeling in image analysis. Springer Science & Business Media; 2009.

[25] Hathaway RJ, Bezdek JC, Pedrycz W. A parametric model for fusing heterogeneous fuzzy data. IEEE transactions on Fuzzy Systems. 1996;4(3):270-281.

[26] Wen W, Xia A. Verifying edges for visual inspection purposes. Pattern recognition letters. 1999;20(3):315-328.

[27] Kumar A, Ghosh S, Dadhwal V. Sub-pixel land cover mapping: SMIC system. ISPRS Int. Sym “Geospatial Databases for Sustainable Development. Goa, India; 2006.

[28] Binaghi E, Brivio PA, Ghezzi P, Rampini A. A fuzzy set-based accuracy assessment of soft classification. Pattern recognition letters. 1999;20(9):935-948.

[29] Silván-Cárdenas JL, Wang L. Sub-pixel confusion–uncertainty matrix for assessing soft classifications. Remote Sensing of Environment. 2008;112(3):1081-1095.
[30] Byju AP. Non-Linear Separation of classes using a Kernel based Fuzzy c -Means (KFCM) Approach. [MSc. Thesis] ITC, University of Twente, The Netherlands; 2015.