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Object Detection and Fuzzy-Based Classification Using UAV Data

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ABSTRACT
UAV (Unmanned Aerial Vehicle) equipped with remote sensing devices can acquire spatial data with a relevant area of interest. In this paper, we have acquired UAV data for high voltage power poles, urban areas and vegetation/trees near power lines. For object classification, the proposed approach based on the fuzzy classifier is compared with the traditional minimum distance classifier and maximum likelihood classifier on our three defined segments of UAV images. The performance evaluation of all the classifiers was based on the statistics parameters which included the mean, standard deviation and PDF (probability density function) of each object present in the image acquired by the UAV and the variances of each channel of the UAV imagery were calculated. The results showed that the fuzzy-based classifier outperformed as compared to the other classifiers. We achieved the classification accuracy of 93% with a Fuzzy-based classifier.

KEY WORDS: Classifier, Fuzzy Logic, Minimum Distance, Orthorectification, Spectral property, Supervised Classifier, UAV.

1 INTRODUCTION

THE civilian applications of UAVs have recently been increased drastically due to the cost reduction and small sizes of the GPS, sensors and processing hardware (J. A. J. Berni, Zarco-Tejada, Sepulcre-Cantó, Fereres, & Villalobos, 2009; Laliberte, Goforth, Steele, & Rango, 2011). Therefore, the UAV's role in remote sensing applications has been increased. Further, with the development of robust, autonomous and small sensors (Nex & Remondino, 2014), UAVs are quickly evolving into stand-alone systems which can provide the required information with high temporal and spatial resolution. It uses an autonomous system (Gageik, Nils, Michael Strohmeier, 2010) with an optical flow sensor for positioning and navigation for the surveillance of ground objects. The UAV equipped with remote sensing devices (Habib, Durdana, Habibullah Jamal, 2013; Hudjakov, Robert, 2013) can now acquire spatial data relevant to land coverage etc. Further this data is used for modeling and analytic processes. The major UAV advantage is that it is possible to get high frequency and high resolution images (Zecha, Link, & Claupein, 2013). To detect and see the fire areas in forests is a very promising application (Qin, 2014) as due to it being quick and there being less risk for video surveillance through helicopters (Honkavaara et al., 2013). A UAV system can provide the effective solution to identify the vegetation and we can also create detailed maps of the vegetation (J. Berni, Zarco-Tejada, Suarez, & Fereres, 2009; Feng, Liu, & Gong, 2015). It is also possible to generate a detailed map of the vegetation grouping at the type of tree level. Therefore, UAV systems equipped with remote sensing devices are used for forest resource management, vegetation monitoring and river monitoring. Traditional pilot-based airborne platform usage is limited due to its expensive operational cost in comparison to satellite-based remote sensing and aerial photogrammetry. UAVs are providing safer and cost minimized data acquisition systems (Herwitz, S. R., 2004). Further, UAVs can fly at a much lower altitude than piloted airborne systems, which results in a very high spatial resolution (Mylonas, Stavrakoudis, Theocharis, & Mastorocostas, 2015). There are several

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works used for the improvement of classification and feature extraction techniques based on remote sensing applications (Mylonas et al., 2015). Mylonas used a fuzzy segmentation method to enhance the spatial representation. This fuzzy-based segmentation was totally based on pixels using a voting strategy of the specific segment. The author (Tuia, Ratle, Pozdnoukhov, & Camps-Valls, 2010) addressed different kernels' functions using an SVM classifier to measure the classification of aerial images. (Hester, Cakir, Nelson, & Khorram, 2008) proposed the iterative self-organizing data analysis technique (ISODATA) by using spectral band features based on very high resolution images and provided an overall accuracy of 89.0% overall. The researchers adopted different feature extraction techniques, including the grey level concurrent matrix (GLCM) (Haralick, Shanmugam, & Dinstein, 1973), the length-width extraction algorithm (LWEA) (Shackelford & Davis, 2003), 3D wavelet analysis (Yoo, Lee, & Kwon, 2009), the differential morphological profile (DMP) (Pesaresi & Benediktsson, 2001) etc. These feature extraction techniques are insufficient to show a good accuracy without using a good classifier in remote sensing applications. The author in (Pacifici, Chini, & Emery, 2009) proposed texture features using a neural network classifier for the classification of very high resolution images, which provided satisfactory accuracy. Shackelford and Davis (Shackelford & Davis, 2003) proposed LWEA features and reported accuracy of more than 80% using UAV images. The author in (Huang & Zhang, 2012) proposed a multi-scale approach using different window sizes and provided reliable spatial representation, and reported an accuracy of 81%. The author in (Vincent, 1993) used a grey-scale morphological reconstruction for remote sensing images by changing different window sizes and improving the classification-based VHR remote sensing data (Benediktsson, Pesaresi, & Arnason, 2003). It can be concluded that the spatial features are not sufficient for object-based classification using remote sensing images. Further, spectral features are used to discriminate the features values using aerial images and a fuzzy-based classifier is sufficient to produce good accuracy with a spectral of statistics features of UAV images.

In this paper, we have acquired UAV data for high voltage power poles, urban areas and vegetation/trees near power lines. Many methods for classification are reported for classifying the UAV data (Pajares, 2015). Here, in this paper, we have proposed a new approach based on the fuzzy classifier which is used for this kind of application. We have further compared our proposed classifier results with the traditional minimum distance classifier and maximum likelihood classifier on our three defined segments of UAV images. The performance evaluation of all the classifiers was based on the statistics parameters which included the mean, standard deviation and PDF (probability density function) of each object present in the image acquired by the UAV and the variances of each channel of the UAV imagery were calculated. Further, we compared the performance graphically. The results showed that the classifier based on fuzzy logic performed better visually as well as analytically based on the spectral as well as statistics features. The fuzzy classifier achieved the maximum classification accuracy of 93% as compared to the maximum likelihood classifier and minimum distance classifier.

2 DATA ACQUISITION

THE system consisted of an air vehicle with a 24.3MB color, infrared, Normalized vegetation index (NDVI), hyperspectral, multispectral or gas spectrometer sensor, a foldable portable take off catapult and rugged ground control station. The battery timing was almost 2 hours. The images acquired had a resolution of almost a half of a centimeter. The system used for our data collection had automatic controlling software as shown in Figure 1. (a, b).

Figure 1. (a) UAV used for the data collection of the area of interest (b) Software for controlling the UAV.

The area of interest contained hills, power transmission poles and power lines, trees, vegetation, shrubs and particularly dangerous trees which could affect the power lines as they were in the way. The ground sample distance (GSD) varied and depended on the height of the UAV. The 5 cm GSD was obtained for the height of 150 meters and 10 cm GSD for the 300 meter height. The maximum height was 2000 meters and the normal height was 700 meters. The ground resolution varied and depended on the height or altitude of the UAV to capture the images. The 15 cm GSD for the height of 700 meters was used in our application and it was a feasible range for our required task. This was the normal range to collect data using a UAV. In our design experiment, the height of 700 meters was used for a 15 km span area in square kilometres.

3 PROPOSED METHOD

WE have acquired UAV images based on our selected area. As the distance was long, the image size was too big. First, segmentation was performed using automatic cropping based on pixel location. The segmented images were further divided into smaller images and cropped into three images from the segmented images based on different scenarios. Further, orthorectification was performed on each small segmented image. The cropping of the images from the original image acquisition and the cropping of the images of the three different cases were of the urban area, hilly area, and the image containing power poles, lines, trees and vegetation. The second image was composed of the power lines, grass, trees, and a small house and the third case contained the image of only the building, roads, and small vehicles. The complete classification based on the fuzzy classifier of the UAV images are described in Figure 2.

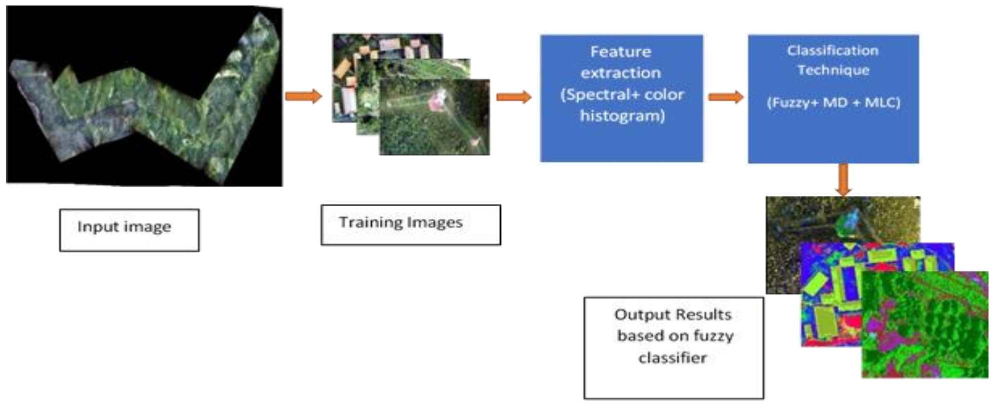


Figure 2. **Flow Diagram of the UAV-based classification.**

For the comparison of our proposed fuzzy-based method with the minimum distance classifier and Maximum Likelihood classifier, the results have been shown in the results section with accuracy.

3.1 Fuzzy Logic Classification

In a Fuzzy-based classifier, fuzzy logic is implemented which requires some fuzzy operators like input membership functions, a fuzzy inference system based on some rules and a fuzzy output membership function. The output classification is in terms of classified pixels, accuracy and the statistics of the classification.

3.2 Fuzzy Logic Design Rule

The Fuzzy Inference System (FIS) Editor shows general information about a fuzzy inference system: The editor acquires the input values from each class variable and produces the output values based on the input values using the if-else condition or built in membership functions. The Membership Function Editor is used to display and edit all membership functions associated with all of the input and output variables for the entire fuzzy inference system. The membership function is used to involve the image classification problems and takes a Gaussian curve for smoothness and non-zero values. The parameters are defined for the membership input functions, which are the mean, standard deviation and average variance, of each class using Matlab’s Fuzzy Logic Toolbox. The signatures used as parameters in the fuzzy logic membership variable come from the signature statistics and indicate green, red or blue for each class’ channel in the mean, standard deviation and average variance values. These values are used as the pattern (parameters) in the FIS (‘fuzzy inference system’) membership function design. The table represents the membership (Stuart, Barratt, & Place, 2006) function values in terms of the variables; m1 represents the membership function for the Power pole class and the green, red and blue channels have been used as the input for this class. The sample areas used for testing displayed very refine results in some areas if the membership function used the average values of variance as shown in Table1. Similarly, the membership function represented for other classes are denoted as m1, m2, m3, m4 and m5. The other class variables were used for training the fuzzy system as shown in Table 2. The membership functions defined for the second image classes were denoted as m6, m7, m8, m9 and m10 and for the third case they were defined as m6a, m7a, m8a, m9a and m10a as shown in Table 3. Based on the explanations of the input (red, green and blue channels) and the output variables (Power pole, Grass, Trees, Power Lines and Land), the rule statements were built in the Rule Editor.

The fuzzy inference system has been developed and defined all of the variables for the membership function and also defined the rules for the necessary classification as shown in Figure 3. The overall fuzzy system used the Mamdani model for sitting and optimizing of membership function. In Fuzzy base classifier, fuzzy logic is implemented which requires some fuzzy operators like input membership functions, fuzzy inference system based on some rules and fuzzy output membership function (Velagic & Osmic, 2013; Wang & Wang, 2016). The output classification is in terms of classified pixels, accuracy and statistics of the classification. The minimum distance to means decision rule is computationally simple and commonly used. When used properly it can result in classification accuracy comparable to other more computationally intensive algorithms such as the maximum likelihood algorithm. The aforementioned classifiers were based primarily on identifying decision boundaries in feature space based on training class multispectral distance measurements. The maximum likelihood decision rule is based on probability. The probability of a pixel belonging to each of a predefined set of m classes is calculated, and the pixel is then assigned to the class for which the probability is the highest. The maximum likelihood decision rule is one of the most widely used supervised classification algorithms (Castillo & Cervantes, 2014). The maximum likelihood procedure assumes that the training data statistics for each class in each band are normally distributed (Gaussian). Training data with bi- or n-modal histograms in a single band are not ideal. In such cases the individual modes probably represent unique classes that should be trained upon individually and labelled as separate training classes. This should then produce unimodal, Gaussian training class statistics that fulfill the normal distribution requirement. The rule statement for the second image class variables were defined in the Rule Editor for the image classification and described the input variable (red, green and blue channels) and output variables (Buildings, Trees, Roads, Shads and Grass) in verbose format. The rules for the image classification procedure in verbose format were as follows:

Table 1. **The decision rule for image classification for case 1.**

IF (GREEN is m1) AND (RED is m1) AND (BLUE is m1) THEN (class is Power pole)
IF (GREEN is m2) AND (RED is m2) AND (BLUE is m2) THEN (class is Grass)
IF (GREEN is m3) AND (RED is m3) AND (BLUE is m3) THEN (class is Trees)
IF (GREEN is m4) AND (RED is m4) AND (BLUE is m4) THEN (class is Power Lines)
IF (GREEN is m5) AND (RED is mf5) AND (BLUE is m5) THEN (class is Land)

Table 2. **The decision rule for image classification for case 2.**

IF (GREEN is m6) AND (RED is m6) AND (BLUE is m6) THEN (class is Buildings)
IF (GREEN is m7) AND (RED is m7) AND (BLUE is m7) THEN (class is Trees)
IF (GREEN is m8) AND (RED is m8) AND (BLUE is m8) THEN (class is Roads)
IF (GREEN is m9) AND (RED is m9) AND (BLUE is m9) THEN (class is Shads)
IF (GREEN is m10) AND (RED is m10) AND (BLUE is m10) THEN (class is Grass)

Rules for the image classification procedure in verbose format based on the descriptions of the input (red, green and blue channels) and output variables (Trees, Power Lines, House, Land and Grass) were as shown in the following:

Table 3. **The decision rule for image classification for case 3.**

IF (GREEN is m6a) AND (RED is m6a) AND (BLUE is m6a) THEN (class is Trees)
IF (GREEN is m7a) AND (RED is m7a) AND (BLUE is m7a) THEN (class is Power Lines)
IF (GREEN is m8a) AND (RED is m8a) AND (BLUE is m8a) THEN (class is House)
IF (GREEN is m9a) AND (RED is m9a) AND (BLUE is m9a) THEN (class is Land)
IF (GREEN is m10a) AND (RED is m10a) AND (BLUE is m10a) THEN (class is Grass)

4 RESULTS

THERE have been three cases discussed for the assessment of the fuzzy classifier and later they were compared with the minimum distance classifier and maximum likelihood classifier. The first case contained the segment of the image of the Power pole, Grass, Trees, Power Lines and Land. The second segment of the image contained the buildings, Trees, Roads, Shads and Grass. The third segment of the image had a number of objects contained therein: Trees, Power Lines, House, Land and Grass. The three different cases of the segments were proposed to analyse which area of the UAV images produced more accuracy and how we could identify the power lines and power transmission poles based on the UAV images using different classifiers based on the spectral as well as color signature of the images. The results were produced using the fuzzy logic classifier as well as existing classifiers on three different cases as shown in Figure 4. The (a, b, c), Figure 5 (a, b, c) and Figure 6. Classification (a, b, c). Figure 4. The showed the classification results based on the fuzzy and other classifiers using an urban area. The results were more prominent in the urban area based on the distinct features of the objects like buildings, roads, parks etc. The features were not more prominent in the third case segment of the image, analytically, as shown in Figure 6. Classification. In conclusion, the classification map based on the fuzzy system produced more accuracy as compared to other maps generated by the minimum distance and maximum likelihood classifier as shown in Figure 4. The (a), Figure 5 (a) and Figure 6. Classification (a).

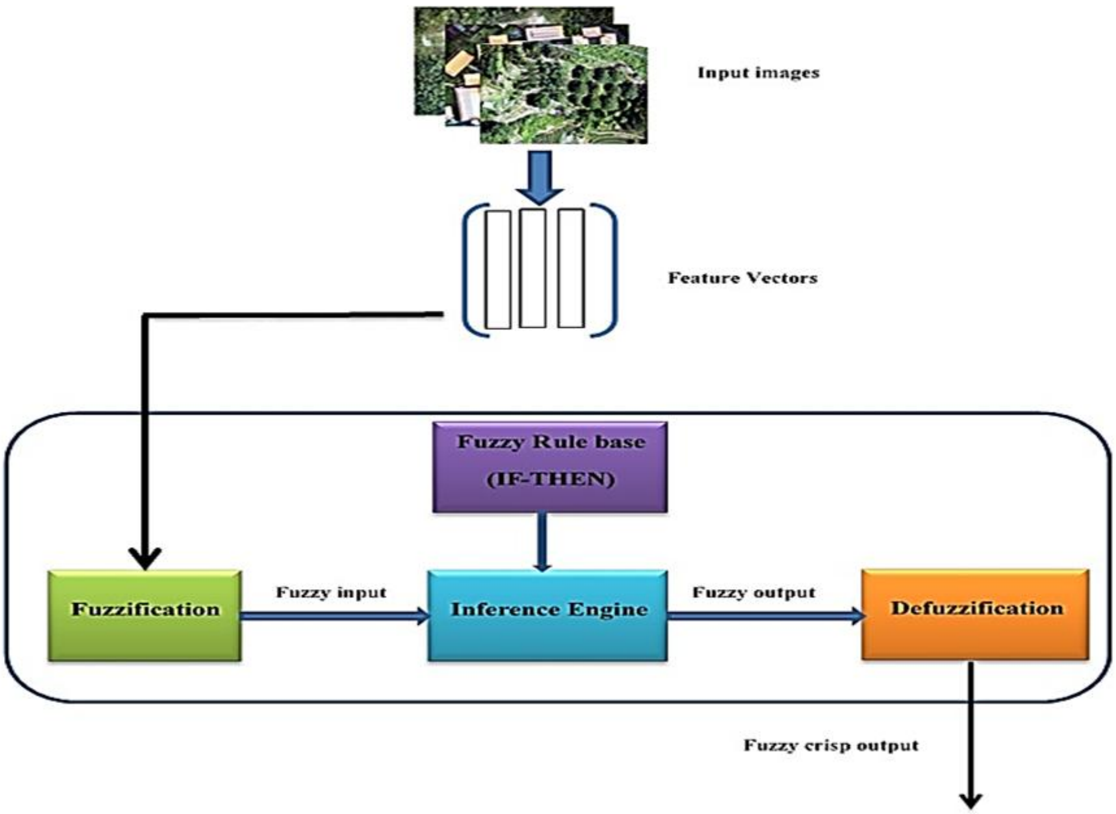


Figure 3. The proposed system based on feature extraction and classification.

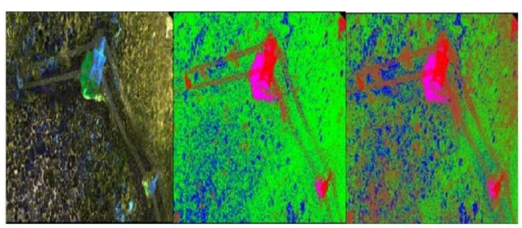


Figure 4. The Classification of the UAV image based on five different classes of a non-Urban area: a) the Fuzzy classification approach, b) using the minimum distance classifier approach and c) the maximum likelihood classifier approach.

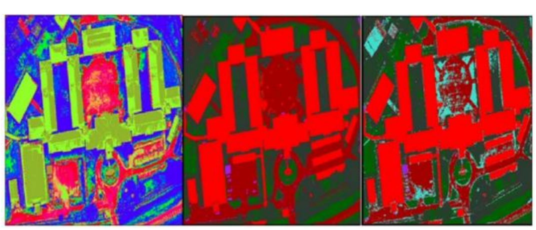


Figure 5. Classification of the UAV image based on five different classes of an urban area using: a) the fuzzy classification approach, b) the minimum distance classifier approach and c) the maximum likelihood classifier approach.

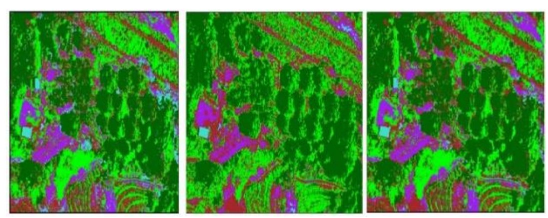


Figure 6. Classification of the UAV image based on five different classes of buildings, power lines, trees and land area using: a) the fuzzy classification approach, b) the minimum distance classifier approach and c) the maximum likelihood classifier approach.

In Table 4, the signatures used as a training vector in each class of the images were based on the mean, standard deviation and covariance of each channel of each class using a hilly area's UAV images. The average value of covariance for each channel was used as a training sample. The signature statistics gave a list of each of the classes, with the mean values and standard deviations for each channel for the class selected. These data were used in the definition of the membership function for the fuzzy classification. Similarly, the training samples for the urban and non-urban images are shown in Table 5 and Table 6.

Table 4. Training values based on color features using Hilly UAV images.

Classes	Channels	Mean	STD	Variance		
Power pole	Red (m1)	171.571	23.384	546.819	556.371	57.681
	Green (m1)	152.086	23.585	478.371	556.243	625.159
	Blue (m1)	171.187	27.752	575.681	625.159	770.201
Grass	Red (m2)	104.765	19.177	367.770	294.020	259.582
	Green (m2)	105.607	17.219	294.020	296.492	222.348
	Blue (m2)	95.877	14.856	259.582	222.348	220.708
Trees	Red (m3)	110.270	19.158	367.027	303.836	185.742
	Green (m3)	112.586	16.923	303.836	286.398	170.294
	Blue (m3)	95.869	14.267	185.742	170.294	203.539
Power Lines	Red (m4)	128.441	30.169	910.181	607.127	752.916
	Green (m4)	120.451	23.096	607.127	533.435	565.031
	Blue (m4)	122.355	27.122	752.916	565.031	735.593
Land	Red (m5)	178.215	12.549	157.470	104.237	94.954
	Green (m5)	127.430	9.605	104.237	92.249	68.114
	Blue (m5)	143.687	9.801	94.954	68.114	96.050

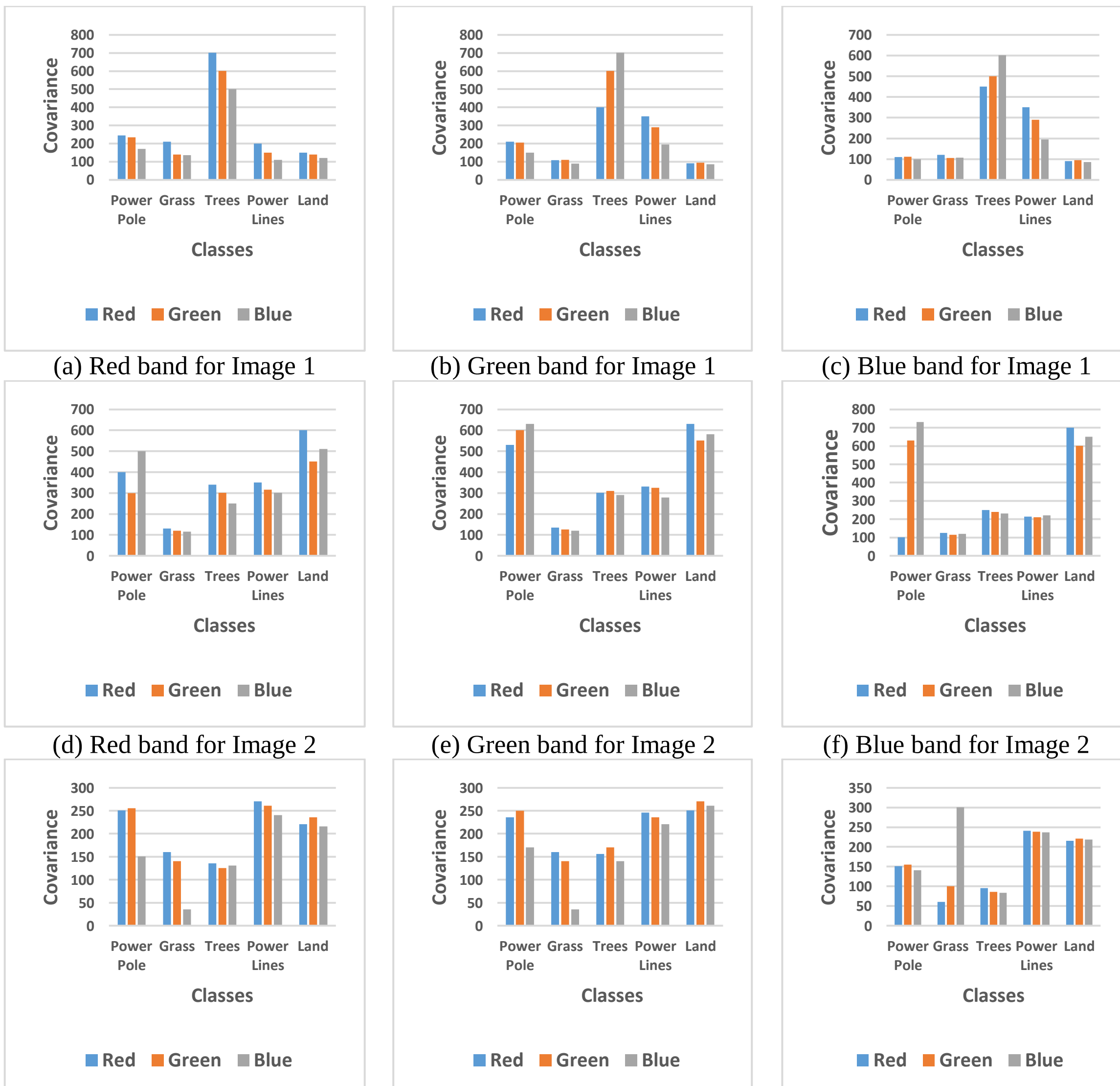
Table 5. Training values based on color features using the Urban UAV images.

Classes	Channels	Mean	STD	Variance		
Power pole	Red (m6)	171.571	23.384	546.819	556.371	57.681
	Green (m6)	152.086	23.585	478.371	556.243	625.159
	Blue (m6)	171.187	27.752	575.681	625.159	770.201
Grass	Red (m7)	104.765	19.177	367.770	294.020	259.582
	Green (m7)	105.607	17.219	294.020	296.492	222.348
	Blue (m7)	95.877	14.856	259.582	222.348	220.708
Trees	Red (m8)	110.270	19.158	367.027	303.836	185.742
	Green (m8)	112.586	16.923	303.836	286.398	170.294
	Blue (m8)	95.869	14.267	185.742	170.294	203.539
Power Lines	Red (m9)	128.441	30.169	910.181	607.127	752.916
	Green (m9)	120.451	23.096	607.127	533.435	565.031
	Blue (m9)	122.355	27.122	752.916	565.031	735.593
Land	Red (m10)	178.215	12.549	157.470	104.237	94.954
	Green (m10)	127.430	9.605	104.237	92.249	68.114
	Blue (m10)	143.687	9.801	94.954	68.114	96.050

Table 6. Training values based on color features using the Non-Urban UAV images.

Classes	Channels	Mean	STD	Variance		
Buildings	Red (m6a)	210.517	12.474	155.610	121.491	13.469
	Green (m6a)	144.253	11.857	121.491	140.595	104.575
	Blue (m6a)	138.489	16.606	13.469	104.575	275.757
Trees	Red (m7a)	47.507	15.453	238.794	89.957	77.857
	Green (m7a)	60.627	15.879	236.033	252.155	155.923
	Blue (m7a)	47.380	11.155	150.330	155.923	124.435
Roads	Red (m8a)	102.860	15.842	250.967	238.591	232.004
	Green (m8a)	96.992	15.222	238.591	231.171	223.431
	Blue (m8a)	111.052	14.832	232.004	223.431	219.987
Shads	Red (m9a)	214.919	15.161	229.870	238.922	206.703
	Green (m9a)	217.919	16.034	238.922	257.091	224.081
	Blue (m9a)	232.413	14.239	206.703	224.081	202.750
Grass	Red (m10a)	84.814	11.471	131.591	89.957	77.857
	Green(m10a)	92.523	8.555	89.957	73.190	58.088
	Blue (m10a)	63.263	7.480	77.857	58.088	155.948

In determination of whether the training areas that have been selected were well represented, a histogram was used: if the histogram has a single peak, then the training area was distinct and there was no confusion between it and another training area. A histogram with a bimodal distribution would indicate that there was an ambiguity between the current and some other class. The peak histogram values of each channel in each band had a significant value as shown in Figure 7 in the case of using the fuzzy logic classifier. The discriminate factor of each histogram value used the covariance value of each band in the spectral features. The spectral signatures can be determined based on the statistical parameters in the aerial images. The characteristics of spectral signature are determined using the mean, standard deviation and covariance of each aerial images as shown in the Table 4, Table 5 and Table 6.



(a) Red band for Image 1 (b) Green band for Image 1 (c) Blue band for Image 1

(d) Red band for Image 2 (e) Green band for Image 2 (f) Blue band for Image 2

(g) Red band for Image 3 (h) Green band for Image 3 (i) Blue band for Image 3

Figure 7. The covariance comparison of different channels of the UAV images for three segments. Each segment contains five classes and shows the histogram of the covariance values of each class of each channel, (a-c) covariance of each channels for Image 1, (d-f) covariance of each channels for Image 2, (g-i) covariance of each channels for Image 3.

The covariance of each channel in the first image segment shows that the histogram covariance value of class three was very high as compared to the other classes. The other classes' values were almost the same and showed an overlapping area of all classes. The covariance values in segment two shows that the power poles and power lines had discriminate high values as compared to other classes and segment three provides the information of the roads and shades, providing high covariance values in each channel of the image. This provides the statistical analysis of the different classes of the UAV images. Our interest in power lines, power poles and buildings has been mentioned above for all cases.

The fuzzy logic classifier gave more accuracy as compared to the existing machine learning algorithms, such as the maximum likelihood classifier and minimum distance classifier as shown in Figure 8. .

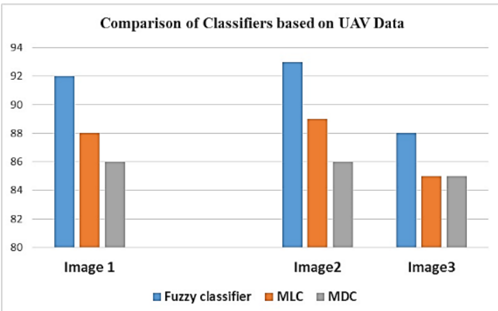


Figure 8. Comparison of the classification values using the UAV's images of three types.

5 DISCUSSION

THE proposed method based on fuzzy system (FS) provides better accuracy because this classifier handle the hard and soft feature space labels. Although FS were designed based on linguistic and expert knowledge, the so-called data-driven approaches have become dominant in the fuzzy systems design area, providing results comparable to other alternative approaches (such as ANNs and SVMs), but with the advantage of greater transparency and interpretability of results. In FS systems, typically, the features are associated with linguistic labels (e.g., low, normal, high). These values are represented as fuzzy sets on the feature axes and that's the reason our proposed classifier based on fuzzy system has comparatively good performance as compared to other classifier. The three different classifiers have been evaluated based on the aerial UAV remote sensing images. The fuzzy based classifier has been proposed for object classification and proposed classifier provided more accuracy as compared to the existing classifiers. The accuracy of the Fuzzy logic classification was 92 %, the accuracy of the maximum likelihood classifier was 88% and the minimum distance classifier's accuracy was 86% for the first image. The accuracy in the second case was 93% using the fuzzy logic classification; it provided the highest accuracy in that image segment which belonged to the urban area image. Finally, in the third case, it was 88% based on the fuzzy logic classifier as compared to the other classifiers due to less discrimination of the green channel values. The peak value of the histogram of the spectral features (mean, standard deviation and covariance of each band) was used to discriminate the feature values. The lower the peak meant that this spectral feature provided less discrimination and the higher the spectral feature value meant that it provided the higher histogram values. This relation was also affected when some spectral feature values had an overlapping area. The fuzzy logic classifier produced more accuracy due to less of an overlapping area between the spectral features based on the color values of each band with the inclusion of the green band. Similarly, the k means classifier was based on the cluster value of the input data and due to the overlapping between some color features providing less discrimination in the k means minimum distance classifier. The same was repeated in the maximum likelihood classifier with very less difference.

6 CONCLUSION

IN this paper, we classified the UAV imagery using the machine learning algorithms and compared the performance with the proposed fuzzy logic classifier. It performed well as compared to the traditional classifiers. The results show that the UAV images are the better choice for aerial surveillance to monitor different applications particularly the monitoring of vegetation and trees near power poles using spectral features. The spectral features are very reliable and provide good classification results in case of using the fuzzy classifier. The objective of this study has been to investigate the detection pattern in UAV-based images and further requires the exploration of which features are best to use for classification. It can be concluded that the UAV is the suitable and reliable source of image acquisition in remote the sensing community and can be used to monitor and detect the vegetation, and power poles near or under trees. In future, we will further investigate the other features using UAV imagery and will apply different machine learning algorithms for monitoring and surveillance applications based on very high resolution UAV images.

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8 DISCLOSURE STATEMENT

NO potential conflict of interest was reported by the authors.

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