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Advances in Classification Techniques for Semi Urban Land Features using High Resolution Satellite Data

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Abstract Classification of satellite Images is one of the major research areas in remote sensing fields. Classification of remote sensed data is required for accurate classification of semi urban land features. Satellite image classification plays an essential role in proper monitoring and management of natural and manmade resources on the earth surface. However a good data set is required for the accurate classification of remotely sensed data. In this paper, to classify the data set, various image fusion techniques are used for fusing high resolution Panchromatic data with low resolution Multi-spectral data which gives better quality and more informative image data set. The performances of different fusion techniques are then evaluated to identify the best possible technique which gives better result for image classification.
Keywords *Remote Sensing; Image Fusion; High Resolution; Image Classification; Panchromatic; Multispectral*

1. Introduction

Remote sensing is the advancement in technique to obtain relevant data about earth's surface without being in direct contact with it. Sensors are used to receive and record information about an object without having any physical contact with it. These sensors are mounted on aerial vehicles like helicopters, planes, and satellites, and record the electromagnetic energy reflected from the objects surface. Unmanned aerial vehicles with sensors are also used to capture images remotely from earth surface.

With the availability of high quality satellite images and with improved image enhancement techniques, remote sensing technique has rapidly advanced over the years. Remote sensing science has always been an interesting topic over the years, and with the arrival of the earth observation satellite equipped with advanced instruments to monitor closely the land-air-ocean interactions, the field has expanded dramatically in the recent past. Due to the technical limitations of remote sensing satellites, they do not capture both high spatial and spectral images at the same time. Instead, dual images are captured;

one is a high resolution panchromatic image, which is used for identifying spatial details, and the other is a low resolution multispectral image, which is suitable for detecting spectral properties of image. The process of integrating high resolution panchromatic image with low resolution multispectral image is called Image fusion technique. The resultant fused image will be more informative and having better quality as compared to original multispectral data.

Usually image data is obtained from different types of camera with the region of interest (ROI) being the same. The quality of the image depends upon type of camera and its resolution. However to classify different objects in a scene, it is necessary to have a very high resolution camera. An alternative way to extract more information from the same region of interest is to fuse the images. Therefore, fusion techniques play an important role in getting a high quality image. Different fusion techniques have been adopted in RS data processing and the process results in the extraction of abundant information from the fused data. Hence, in our methodology we consider image data of different resolution of the same area and the images are panchromatic and multi-spectral image of the ROI.

Image fusion is a process of integrating two or more images to form a new and composite image using a certain algorithm in order to obtain more information than that can be derived from each of the single sensor data alone [1] [2]. In remote sensing, the fusion of a high resolution panchromatic (PAN) image with a low resolution multi-spectral (MS) image to produce a high resolution multi-spectral image. The PAN images have a very high spatial content while the MS images provide high spectral information. The main aim of fusing PAN and MS images is to create composite images of enhanced interpretability. The resultant image is a new image which is more suitable for human and machine perception or further image processing tasks such as segmentation, feature extraction and object recognition.

Several image fusion techniques are developed to improve the quality of a remote sensed data. The most commonly employed traditional fusion techniques are: Addition and Multiplication fusion, Transformation fusion, Filter fusion, and Multi-resolution analysis is also under investigation. In general, remote sensing fusion techniques can be classified into three different levels: The pixel/data level, the feature level and the decision level [1].

Pixel level is a low level of fusion which is used to analyze and combine data from different sources before original information is estimated and recognized. The pixel-level method works either in the spatial domain or in the transform domain. Feature level is a middle level of fusion which extracts important features from an image like shape, length, edges, segments and direction. Decision level fusion uses the outputs of initial object detection and classification as inputs to the fusion algorithm to perform the data integration. The most common and conventional fusion techniques are Principal Component Analysis (PCA), Intensity-Hue-Saturation (IHS) method, Brovey Transform (BT) and Multiplicative method (MT); currently the Wavelet Transformation method is widely used for study. Existing transformation based image fusion methods available are additive and multiplicative technique, multi-resolution method, filters fusion method, fusion based on inter-band relation [3].

Padwick et al. (2010) compared IHS, PCA, Gram Schmidt, and HCS (Hyperspherical Color Sharpening) algorithms for fusing WorldView-2 Pan and MS images and confirmed that Gram Schmidt, PCA, and IHS do not produce acceptable pan-sharpened natural colour MS images [4].

Luo and Kay (1988) introduced a generic data fusion structure based on multi-sensor integration. In this system, data from various sources were combined within embedded fusion centres in a hierarchical manner. They made a clear distinction between multisensory integration and multi-sensor fusion [6].

Chavez et al. (1991) applied IHS, PCA, HPF methods to merge multi-spectral and multi-resolution data, viz. Landsat TM (30m) and SPOT panchromatic (10m), and compared the methods [10]. The authors observed that IHS method distorts the spectral characteristics the most, PCA method distorts less while the HPF method distorts the data the least. An experiment conducted by Zhijun et al. (2005) on IKONOS-2 (1m) images too confirmed that the IHS, BT and PCA methods distort the spectral characteristics more than HPF, HPM, ATW and MRAIM methods [10].

Yun Zhang (2002) observes that the conventional fusion algorithms which have been successful for fusion of data from a particular sensor cannot effectively fulfil the fusion of the images collected from some other sensors [14].

Finally, it is also observed by the reviewers that the majority of the studies have shown greater concern for developing and evaluating fusion techniques using statistical metrics rather than developing application-specific techniques and assessments.

Image classification is viewed as the process of automatic categorization of all the pixels in an image into a finite number of land use/land cover classes (LU/LC). For example, LU built-up-land, building, road, for LC i.e., water, agriculture land forest, etc. Digital image processing techniques, also serves as a powerful quantitative data analysis tool for the regional mapping of natural resources. Image classification is a complex process that may be affected by many other factors. Effective use of multiple features of remotely sensed data and selection of suitable classification method play dominant role in improving classification accuracy. Non parametric classifiers such as fuzzy logic, neural network, decision tree classifier and knowledge based classifiers are the important approaches used by research scholars in recent years.

In general image classification can be grouped as

- Supervised and unsupervised
- Parametric and non-parametric
- Hard and soft (fuzzy) classification
- Pixel, sub-pixel and per-field classifications

Conventionally, the classification is based on “one-pixel-one-class relationship” i.e., obtaining a unique relationship between a given material or land cover class and its reflected radiation (reflectance) at certain wavelength contained in a spectral band of an image. It is commonly known as “hard” classification and is broadly grouped into two types: (i) Unsupervised classification (ii) Supervised classification. But the conventional methods such as Parallelepiped, Minimum Distance-to-Means, Mahalanobis distance, Maximum Likelihood Classifier, and Iterative Self-Organizing Data Analysis Technique (ISODATA) *only utilize spectral information,* and consequently have limited success in classifying high-resolution urban multi-spectral images for the reasons mentioned.

The Maximum Likelihood Classification (MLC) can obtain minimum classification error under the assumption that the spectral data of each class is normally (Gaussian) distributed. Under this assumption, the distribution of a category response pattern can be completely described by the mean vector and the covariance matrix, and the computation of the statistical probability of a given pixel value being a member of a particular land cover class is made. These probability density functions are used to classify an unidentified pixel. In theory, MLC is the most accurate technique, but slow in computation, and complex in mathematics. The MLC method itself cannot solve the problem of *spectral confusion*.

The principal drawback of the MLC is the assumption of normal distribution of data and requirement of large number of computations to classify each pixel particularly when a large number of spectral channels are involved or a large number of spectral classes need to be differentiated. This poses problem when the ancillary data are added to the classification process since they violate the assumption of normal distribution of the training samples and give rise to multimodal distribution of data. However, the strength of the MLC is that it is not sensitive to sample size, and ensures medium accuracy which makes it adopt to various land cover classification, whereas its counterparts Classification And Regression Tree and Back Propagation Neural Network need adequate and good quality training samples.

Artificial Neural Networks (ANNs) also have been used in the field of image classification by many research scholars [16], [17], [18]. Back-Propagation (BP) algorithm is the most commonly used technique in ANN. Empirical evaluation has revealed that ANN is superior to the statistical methods used in terms of classification accuracy of training data but the classification time in neural network based classifier is linearly proportional to the size of the image. Even though this problem could be greatly reduced by implementing an adaptive back-propagation method and making classification faster, the main drawback of the network technique is its slow training phase [19].

Adoption of fuzzy concept as well as neuro-fuzzy classifiers attempts to resolve ambiguities that exists in RS classification and also increase classification accuracy [29], [21], [31]. Even though fuzzy classifiers exhibit satisfactory results, it is intuitive that they are mathematically complex and are not at ease in implementation. In complex fuzzy systems, manual determination and optimization of fuzzy membership parameters is highly difficult. Object-based classification has also been investigated extensively in remote sensing, but it demands for advanced segmentation techniques prior to classification.

Another promising classifier is Decision Tree (DT). DT classifiers are used successfully in many areas such as radar signal classification, character recognition, remote sensing, medical diagnosis, expert systems, speech recognition etc. This machine learning algorithm, based on “divide and conquer” strategy is a non-parametric classifier. Different variables and split-rules are used to split the subsets into further subsets.

For classification of features in urban area, the expected spatial resolution should be at least 5 m where buildings and roads can easily be distinguished. Following the enhanced spectral and spatial resolution of the sensors, the classification of urban and semi urban area is identified as one of the most challenging tasks in remote sensing for the following reasons. The classification accuracy is a function of two counteracting issues. The first issue is that the finer the spatial resolution the lesser the number of mixed pixels; however, this factor should increase the classification accuracy. But, on contrary to this, the finer the spatial resolution, the larger the number of detectable sub classes which implies that high within-class spectral variance of some classes decrease their spectral separability resulting in decrease in the classification accuracy. Because, the most of the urban land cover types such as roads, buildings, parking lots, grass, trees, shrubs and soil show spectral similarity. As the resolution is increased, the data exhibits abundant texture information and it becomes difficult to distinguish some geographical objects when area of interest has complicated texture information. Also, the spectral characteristic shows uncertainty if the geographical objects have complicated surroundings.

The existing traditional hard classification techniques are parametric in nature and they expect datasets to follow Gaussian distribution. Therefore hard classifiers exhibit lower accuracy in high resolution data where the assumption of Gaussian distribution of spectra is often violated, especially in the complex landscapes in high-resolution data. Another drawback of the parametric classifiers lies in the difficulty of integrating spectral data with ancillary data like digital elevation model, slope, surface temperature, texture and contextual information, etc as most of them are non-Gaussian in nature.

Therefore, parametric classifiers do not ensure of exploiting the best use of the information available through advanced sensor systems and various ancillary data at higher resolution.

The solution to the above problem is to go for the non-parametric classifiers. When non-parametric soft classification approach is proposed the ANN, Support Vector Machines (SVM), Decision Trees (DTs) and Fuzzy Soft Classifiers do gain importance. However, despite the fact that ANN and SVM show superior learning accuracy, they suffer from longer training time. This has made the rule based decision tree algorithms and fuzzy soft classifiers are attractive and promising approaches in classifying the spectrally overlapping classes [28].

Soft classifiers can be useful in describing forest boundaries, shorelines and other continuous classes. They can also bring out objects that cover small areas, which with conventional classifiers otherwise would have disappeared. In training and testing in a classification, mixed pixels are usually avoided. But it may be difficult to acquire a training set of an appropriate size if only pure pixels are selected for training, since large homogenous regions of each class are needed in the image. The training statistics defined, may not be fully representative of the classes and so provide a poor base for the remainder of the analysis.

2. Materials and Methods

2.1. Study Area and Data Characteristics

The study area considered for our work is Mangalore coastal region situated in Dakshina Kannada District, Karnataka State, India at geographical coordinates 13°00'41.5" N latitude and 74°47'35" E longitude as shown in Figure 1. The area considered for investigation is intensive and is dominated by agricultural, urban and tourism activities. It has a good mixture of classes comprising of man-made structures like concrete buildings, residential areas, roads, National highway, pool, and natural land cover features like barren land, coastal dunes, afforestation, wetlands, shrubs, sea and sea shore, etc. Also, the diverse environmental structures such as geology, soil, climate, hydrology and vegetation interact strongly with these land cover activities. This place is well connected to various important cities in the state via bus, rail and air. Moreover, the township is undergoing continuous changes over the past few years and hence selected for the study.

The image dimension of the study area is 277x255 pixels in MS data and 658x609 pixels in pan-sharpened data. Table 1 gives the specification of the image data products that has been used in the study. The data are of LISS-IV (Linear Mapping and Self Scanning) sensor of IRS P-6 (Indian Remote Sensing Satellite), Multi-spectral bands in Green, Red, Infrared and Blue.

Figure 1: *Study Area: Mangalore Coastal Region, Dakshina Kannada District, Karnataka State, India*

2.2. Evaluation of Image Fusion Techniques

In our research work, five different fusion techniques have been applied on the data set under study. Based on their performance, the best candidate is selected for fusing the MS and panchromatic data for the study of classification algorithms.

- Brovey Transform (BT)
- Principal Component Analysis (PCA)
- Multiplicative Technique (MT)
- Intensity Hue Saturation (IHS)
- High Pass Filtering (HPF)

2.3. Study of Classification Techniques

The motivation behind this research is the fact that accurate classification of remotely sensed data into various LU/LC is very essential in proper management and monitoring of natural as well as man-made resources on the Earth. The aim of this research is to improve the classification accuracy over semi-urban LU/LC features in high resolution satellite image by adopting soft classification algorithms and exploiting the spatial information inherent to the high resolution data.

3. Results and Discussion

The objective of evaluation of image fusion techniques is to determine the best fused data for classification of semi-urban LU/ LC features. Hence, the objective has been framed to carry out image fusion to integrate a multi-spectral image of 5.8 m and a panchromatic image of 2.5 m spatial resolution at pixel level by employing five of the commonly available data fusion algorithms and to evaluate the algorithms based on visual and statistical analysis, and finally substantiate the findings with classification accuracy.

3.1. Visual Analysis

Visual comparison of all the fused images has been used for the qualitative assessment since it is the most simple but very effective tool. When all the pan-sharpened images are compared visually with the original MS image, as far as the spatial quality is concerned, it is apparent that the spatial resolution of the resultant/ fused images is higher than the original MS image and it is comparable to the resolution of the original PAN image. A few small and fine urban features such as roads, building edges, vehicles on high-way, flag post in front of the main building, slope of the roof, building shadows, separation between the buildings, individual tree crowns, array of trees in coconut farm etc. that are not discernible in the original 5.8m resolution MS image are identified individually in all the fused images. Other large features such as pools, tree clusters, roads and building blocks are much sharper than those seen in the original MS image.

3.2. Quantitative Analysis

The statistical analysis is necessary in order to examine the spectral information preservation in the resultant fused image. Therefore, mean value and the standard deviation were studied for all the fused images.

Table 1: *Histogram-Means of the Bands of the Fused Images*

	MS	PCA	BT	MT	HIS	HPF	PAN
Band 1	107.5	49.4	43.3	30.5	107.4	107	79.25
Band 2	75.5	110.9	41.2	42.2	115	75	
Band 3	115.3	47.5	40.8	29.6	75.4	114.8	
Column Average	**99.43**	**69.26**	**41.76**	**34.1**	**99.26**	**98.93**	

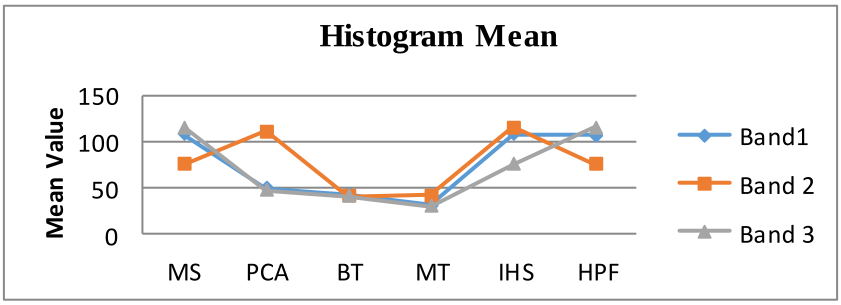

Figure 2: *Histogram Means of Fused Image*

From Figure 3 it is observed that in Band-1, the mean value is maximum for MS, HIS and HPF technique - while it is almost same for BT, MT and PCA techniques. In Band-2, the mean values are same for MS and HPF techniques - while it is almost same and it is maximum for PCA and HIS techniques. The mean values are minimum for BT and MT techniques. In Band-3, the mean values are maximum for MS and HPF techniques and it is most minimum for MT technique.

Standard deviation (SD) is an important index to measure the information content in any image. It reflects the deviation degree of values relative to the mean of the image. The computation of standard deviation of the original image and the fused images are carried out band-wise and is indicated in Table 2. Figure 3 shows graphical representation of standard deviation of all the bands of the MS and the fused images.

Table 2: *Standard Deviation of the Bands of the Fused Images*

	MS	PCA	BT	MT	HIS	HPF	PAN
Band 1	27.3	26.3	30.2	29.9	29.2	27.4	26.92
Band 2	15.3	41.7	20.2	26.7	20.8	15.4	
Band 3	17.7	22.5	23.8	25.9	14.7	17.8	
Column average	**20.1**	**30.16**	**24.73**	**27.5**	**21.56**	**20.2**	

Band 1: Green, Band 2: Red, Band 3: Infrared

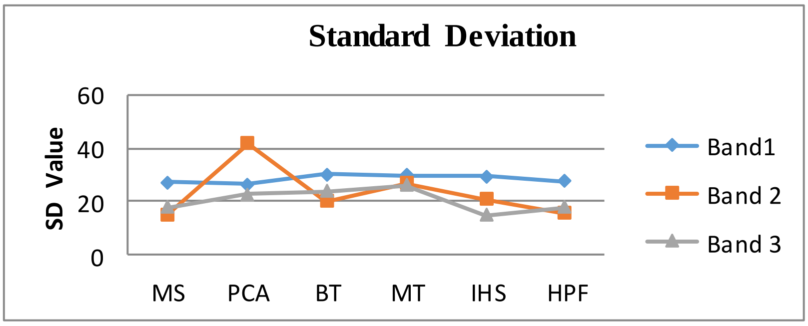

Figure 3: *Standard Deviation of Fused Image*

From the histogram statistics it is revealed that in PCA method, the histogram means of all bands are closer to the corresponding bands in MS bands. The value of SD varies very slightly with respect to MS data. The Multiplicative Technique indicates a major increase in statistical parameters. The Brovey Technique depicts major changes in the statistical parameters as the new pixel values are derived from the ratio of MS band and PAN band data. All the statistical values are found to be at lower end. In HPF fusion technique the mean and SD values are almost equal to the original MS bands. In IHS technique SD values are high, while the mean value remains almost same as that of MS data.

4. Conclusion

High-resolution and multispectral images are an important data source for acquiring large-scale and detailed geospatial information for a variety of applications. Image fusion techniques have proven to be effective tools for providing better image information for visual interpretation, image mapping, and image-based GIS applications.

To obtain better classification results, it is very essential to have a good fused image which retains both spectral and spatial properties of MS and panchromatic images, respectively. In this paper five different techniques are used to evaluate the performance of Image fusion method. Hence, having obtained the best fused image of MS and panchromatic data, the future work will concentrate on developing a classification methodology based on Ant Colony Optimization (ACO) algorithm and evaluate the same with the existing MLC and DT (Decision Tree) classification techniques.

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