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Embedded Zero Tree Wavelet based Artificial Neural Network Image Classification Algorithm - A Study

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Abstract

In this work, an urban area land cover is proposed to classify the large resolution image. It aims to extract the features like texture, shape, size and spectral information in the feature extraction process. Embedded Zero tree Wavelet transform is a lossy image compression algorithm. Most of the coefficients at low bit rates bent through a sub band transform will be zero, or very close to zero. These features data are used for the classification process. Here, we used various classification algorithms namely, Radial Basis Function, SMO, Multilayer Perceptron and Random Forest are implemented. The classification accuracy constantly depends on the efficiency of the extracted features and classification algorithms. The result of the proposed classification algorithms are merged with EZW. Experimental results illustrate that the better accuracy performance is obtained by the Multilayer Perceptron algorithm than other classification algorithms.

Keywords: Artificial Neural Network, Embedded Zero Tree Wavlet, Feature Extraction, Image Classification, Multilayer Perceptron, Radial Basis Function

1. Introduction

Satellite images are used in many applications such as Astronomy and Geosciences information systems. The image received from satellite contains the huge amount of data to be deciphered and to be processed. But our human eye is insensitive to realize subtle changes in the image characteristics such as intensity, color, texture or brightness. So the manual human processing is not successful to retrieve the hidden treasures of information in the satellite image. The optimal solution is the processing of satellite images with digital computers.

Landsat imagery is most consistent and vital earth observation instrument. Landsat imagery is with quite large resolution earth observation data system, which is acquired through sensors. The satellite sensors get large reliability images of earth plane in an efficient approach. Land cover is the physical material at the surface of the earth. It includes grassland, asphalt, trees, bare soil, concrete, etc.

Land cover information executes a vital part in sustainable management, development and exploitation of resources, environmental protection, planning, scientific analysis, monitoring and modeling. Remotely sensed data in particular satellite images, among different advantages such as huge repetitive competencies, several spectral bands or multiple frequency/polarization more effective tools for land cover mapping and they have been adapted widely for land cover monitoring and categorization. Therefore, the challenging tasks are to understand the contribution of each dataset to select the most useful input features. It determines the combined datasets which can maximize the benefits of multisource remote sensing information give the largest classification

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accuracy[1]. However, finite studies have examined way to conclude variables from multi-source information in order to increase the accuracy of classification[2].

2. Feature Extraction

Feature extraction recognizes and extracts remarkable features for a difficult task in order to decrease the complication of processing. Image contains information in an especial impenetrable and difficult form. Image is described by several image features such as color, texture, shape or combination of these features with appealing tie frequency localization and multi-scale properties. Features are distinctive part that separate from different classes. It split into diverse class based on their described properties. A group of features termed as feature vectors or image signatures. This feature vector is assumed to elicitation the related data from the dataset to assist our demands. Image signature acknowledged that image domain outside spectral in order such as temporal, geometrical or image texture field should be utilized so as to tackle the complexity of knowledge mining. It makes perfectly characterize the content of every image of database. It is the process of extracting image features into an obvious extent[3.] It is used to extract the colors, textures and shapes or spectral information. Nowadays, procedures that create use of the lengthy content information of image segments are well fit in remote sensing society[4].

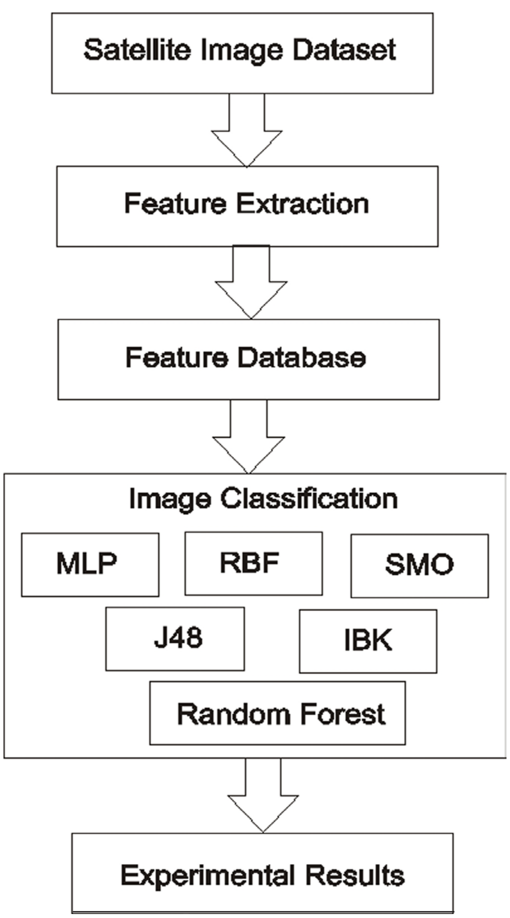

Figure 1. Our system process.

Image analysis can also be helpful once interpreted to construct the surroundings from the Medium Resolution (MR) satellite images[5, 6], wherever urban patterns totally different and primarily specified by the location of streets, buildings and other spaces cannot adequately represented by the spectral standards of a particular pixel. Mean, regular deviation values of every image band, lowest and highest pixel values and standard variation of band index are spectral features of Normalized Difference Vegetation Index (NDVI)[7].

Texture features, which are taken into consideration of closeness associations among pixels. Haralick et al.[8] proposed the GLCM (Gray Level Co-occurrence Matrix) notation and related second-order textural descriptors also. Most commonly used in second-order texture descriptors are borrowed from the GLCM like angular second moment, contrast, correlation or entropy. Analysis of various shape description techniques with mathematical explanations can be founded[9, 10].

Nine Classes based on objects like asphalt, buildings, cars, concrete, grass, pool, shadows, soil and trees, shape based features like border length, border index, compactness, density, length/width, rectangularity, roundness, and shape index. Spectral features are brightness, mean of green, mean of near infrared, mean of red and Normalized Difference Vegetation Index (NDVI). GLCM based texture features are contrast of NIR Band, correlation of NIR band and entropy of NIR band. Standard deviation of green, standard deviation of near infrared and standard deviation of red texture features are extracted.

3. Embedded Zero Tree Wavelet (EZW)

The EZW coding is an easy and efficient continuous image coding algorithm[11]. The EZW steadily construct compression results that are superior just about every known compression algorithms on regular satellite test images. Wavelet based image coding techniques afford substantial

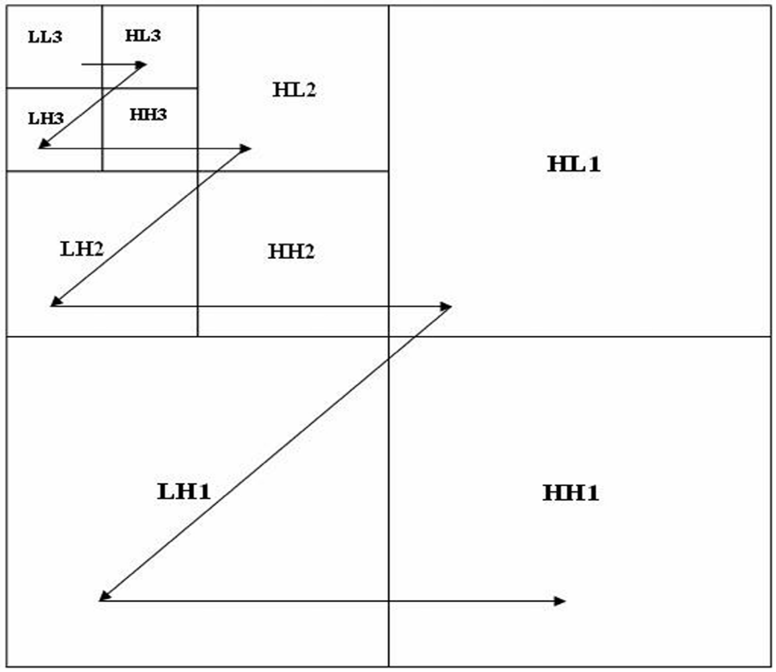

Figure 2. EZW subband structure scanning order.

improvements in picture worth at sophisticated compression ratios[12,13]. The EZW have four concepts:

- A distinct wavelet transform or hierarchical sub band disintegration.
- Prediction in the lack of significant information across scales by taking advantage of the self-similarity natural in images.
- Entropy-coded successive-ballpark figure quantization.
- Universal lossless data compression which is reached via adaptive arithmetic coding.

3.1 EZW Algorithm

3.1.1 Initialization

Set the threshold T to the minimum power of that is greater than max (i,j) |c i,j|/2, where Ci,j are the wavelet coefficients.

3.1.2 Significance Map Coding

Scan all the coefficients in a predefined way and output a symbol when |Ci,j | > T. When the decoder inputs this symbol, it sets Ci,j = ±1.5T.

3.1.3 Refinement

Refine each significant coefficient by sending one more bit of its binary representation. When the decoder obtains this, it boosts the current coefficient significance by ±0.25T.

Set Tk = Tk-1/2, and go to step 2 if more iterations are needed.

4. Image Classification

Image classification automatically assigns an unknown image to a category according to its visual content, which has been a major research direction in computer vision[14]. Appropriate selection of classification algorithms can result in a substantial improvement in the quality of the classification results. The classification algorithms are supported entirely diverse concepts (statistical, nearest neighbor, tree-based). Typically, classifiers are generating training samples for their uses. Earlier, a training data has formalized their own vital structure. Then, Classifier has been trained on each and every numeral of image types and also feature space. The implemented classification algorithms are in briefly represented in the following paragraphs.

4.1 Sequential Minimal Optimization (SMO)

It is a simple and efficient algorithm for work out the quadratic programming problem originating in support vector machines[15]. This algorithm aim to be fast, easy to implement and it has linear memory requirements[16]. It executes the lowest sequential maximization procedure to train a classifier using Gaussian kernels[17]. It also exploits the least feasible quadratic programming issues, which are determine systematically and promptly, normally it improves the scaling and computation time significantly[18].

4.2 Random Forest (RF)

It is an effective prediction tool[19]. It exploit the bagging technique to construct an arbitrarily opt the sample training dataset for every one of the trees. Random Forests are an ensemble classifier[20]. Its novel scheme used to create a classifier model for constructing multiple decision trees, every one of which uses a random selected attribute subset of the full attributes set. Its strengths are recognizing outliers and anomalies in knowledgeable information, exhibiting proximity clusters, forecasting future outcomes, distinctive necessary predictions, recognizing data patterns, interrelating missing values with imputations and providing perceptive graphics[21].

4.3 Multilayer Perceptron (MLP)

It is a simple pattern classifier[22]. It is excellent and balanced learning algorithm[23]. Generally, it has been found in several layers interrelated with feed-forward networks. Every neuron on layer has direct connections to the neurons of the subsequent layer. The neural network read the teaching part by alter the synthetic weight give to the mistake occur in the output level. Back-Propagation algorithm has two major benefits: narrow for modernize the synthetic weights and capable for measure all the fractional outgrowth of the cost function with esteem to these gratis parameters[24].

4.4 Radial Basis Function (RBF)

It has two processing steps[25]. Initial, the input is summarized in the hidden layer among radial activation function based on feed-forward neural networks. Generally, the output layer is a skewed operation of a continuous sequence of hidden outputlayers[26]. The benefit of RBF used to identify the output map using local approximators. Supervised segment has few weights. It's simply a linear combination. This network train very quickly and need less training samples.

5. Experimental Results

5.1 Study Area

The Landsat image of Coimbatore city in India, acquired in the month of May 2014 was used for the analyses. The investigations have been done in the area near the Airport and PSGCAS campus located within latitude: 11° 01 to 11° 30 N, longitude: 76° 95 to 77° 30 and is shown in Figure 3.

5.2 Parameters for Performance Evaluation

Normally, accuracy (overall accuracy, precision and recall) was predicted by training (66%) and testing (34%) for each image type used for performance evaluation. Overall accuracy is specified like the entire numeral of properly classified instances separated by the entire numeral of test instances. Accuracy measures are mean value for all classification. Both testing and training data are used to train the classifiers under a variety of environments, thus build it potential evaluate the virtual act and reliability of the method in favor of a known duty. Precision is the quantity of properly classified examples separated by the numeral of instances labeled by the system as positive. Recall is the numeral of properly classified optimistic

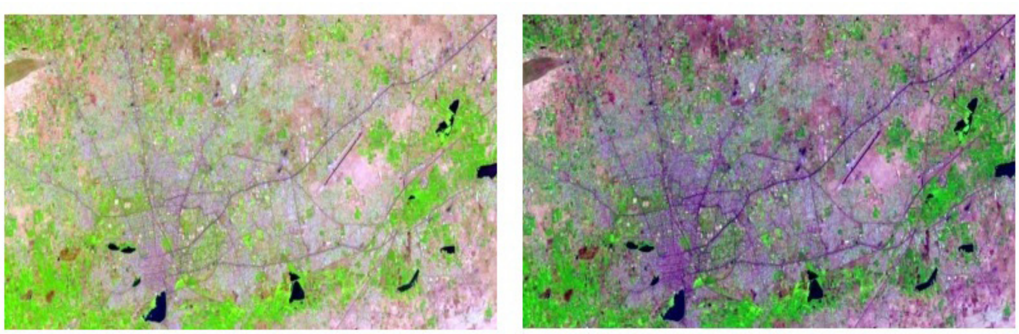

Figure 3. Landsat image of Coimbatore, Tamilnadu, India.

instances separated by the numeral of optimistic instances in the data. It is also referred to as the sensitivity or true optimistic rate or producer's accuracy. Computing overall statistical concurrence of an error matrix, which takes non-diagonal elements into description, is called Kappa statistics.

The various classification algorithm results showed in Table 1. In Table 2 shown the details of EZW based image classification results.

5.3 Graphical Results

The graph results shows that performance analysis related to Accuracy, Kappa Statistic, Precision, and Recall of various classification algorithms and also compared with EZW based image classification results. According to the graphical results that Multilayer Perceptron algorithm has the highest accuracy.

The graph results Figure 4 shows the classification accuracy. EZW based Multilayer Perceptron (MLP) Classifier gets better classification accuracy than any other classifier. The classification accuracy is 79.65% and EZW based image classification accuracy is 82.48%. The graph results Figure 5 shows Kappa Statistic, Precision, Recall values. Here also EZW based Multilayer Perceptron (MLP) is better compare to others.

6. Conclusion

The main goal of this work was focus on image classification strategy in the problem of urban land-cover data.

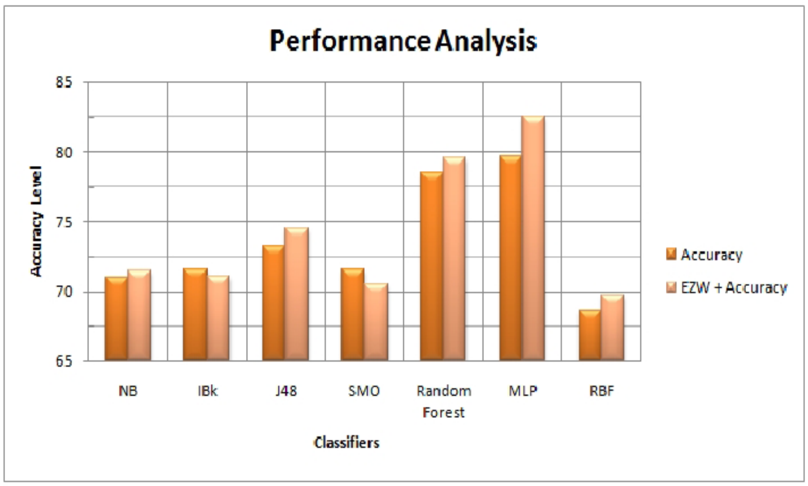

Figure 4. Performance analysis based on classification accuracy with EZW based classification.

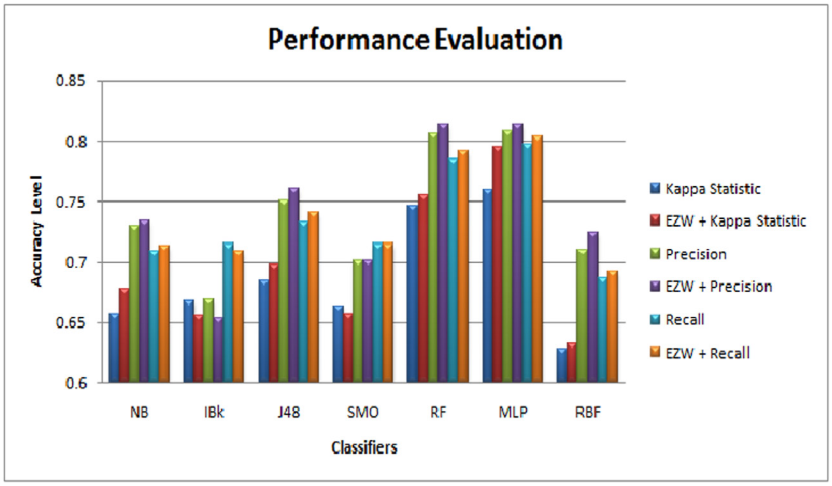

Figure 5. Performance analysis based on kappa statistic, precision and recall with EZW based classification.

Table 1. Details of classification results

Classifiers	Accuracy	Kappa Statistic	Precision	Recall
Naive Bayes	70.9302	0.6569	0.729	0.709
IBk	71.5116	0.6666	0.668	0.715
J48	73.2558	0.6845	0.751	0.733
SMO	71.5116	0.6627	0.701	0.715
Random Forest	78.4884	0.7467	0.806	0.785
MLP	79.6512	0.7601	0.808	0.797
RBF	68.6047	0.6281	0.71	0.686

Table 2. Details of EZW based image classification results

Classifiers	Accuracy	Kappa Statistic	Precision	Recall
Naive Bayes	71.4302	0.6775	0.734	0.713
IBk	71.0401	0.6554	0.654	0.709
J48	74.4998	0.6972	0.761	0.741
SMO	70.5224	0.6569	0.701	0.715
Random Forest	79.5116	0.7557	0.814	0.791
MLP	82.4884	0.7948	0.814	0.804
RBF	69.6512	0.6321	0.724	0.692

Also study of various artificial neural network based image classification methods. The EZW coding is an effective progressive image coding methods. It is mainly considered with reordering. In some cases, discarding lower order coefficients based on some criteria to achieve optimized compression results.

The classification accuracy always depends on the effectiveness of the extracted features and classification algorithm used, SMO, Multilayer Perceptron, Radial Basis Function and Random Forest classification algorithm are used in this study. Then, The result of the proposed classification algorithms are merged with Embedded Zero Tree Wavelet. In this study, we have taken various classification methods and compared the results on the basis of classification accuracy, precision and recall. EZW based Multilayer Perceptron algorithm is better classification accuracy than other algorithms. We can also extent this work to reduce the feature database using dimensionality reduction process.

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