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# Texture Feature Based Satellite Image Classification Scheme Using SVM

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## Abstract

Remote sensing applications have gained considerable research attention now-a-days. Irrespective of the presence of several satellite image applications, there is a constant demand for satellite image classification systems. The satellite image classification system intends to differentiate between the objects being present in the image. It is highly challenging because, the coverage area of the satellite is more, such that the objects appear so small. This makes the process of object differentiation complex. Additionally, the classification accuracy is an important factor, which the classification system must pass through. Taking these challenges into account, this work presents a satellite image classification system, which can classify between the vegetation, soil and water bodies. The objective of this work is met by subdividing the works into three important phases, which are satellite image pre-processing, feature extraction and classification. The image pre-processing phase denoises the image by median filter and the contrast is improved by Contrast Limited Adaptive Histogram Equalization (CLAHE) technique. As the satellite image possess numerous important features, this work extracts multiple features such as first order, GLCM and LWT features. The feature vector is formed out of these features and the classifier SVM is trained. The performance of the proposed approach is observed to be satisfactory in terms of sensitivity, specificity and accuracy.

**Keywords:** remote sensing, satellite image classification, feature extraction

## INTRODUCTION

This Remote sensing is an advanced technology that attempts to study or analyse a specific object space [1]. Basically, the term remote sensing is particularly used for satellite and airborne imagery techniques. The remote sensing technology is categorised by taking the sensing area and imaging sensors into account [2, 3]. Remote sensing technology is the boon to the mankind, as the environmental changes can easily be detected. Some of the noteworthy features of remote sensing technology are that the satellite senses the environment in a spectral range rather than visible range, the atmospheric parameters are studied in a global fashion. These features of remote sensing technology make it applicable for several domains such as environment monitoring and assessement, traffic monitoring and management, transportation planning and management, disaster discovery and so on.

The major goal of the remote sensing technology is to examine certain area with the help of a topographic map. Owing to the advancement of image sensors and imaging technology, it is difficult to classify the areas being present in the sensed topographic trace. This is because of the presence of numerous minute details in the sensed topographic traces. For instance, a single topographic trace may contain vegetation, buildings, sand, pathway, road and so on.

Obviously, human eyes find it difficult to differentiate between a range of numerous atmospheric objects. However, computers can classify between enormous counts of atmospheric objects, provided it has been trained properly. However it is not a simple task to train the machine, as the sensed image contains numerous objects and fine features. Besides this, the computer aided classification should satisfy two important goals, which are accuracy and processing speed.

Taking these points as challenge, this paper intends to present a classification system that can differentiate between vegetation, soil, and water bodies. This kind of classification system can assist the users to plan and manage the agricultural activities, to track the presence of water source, to plan and execute irrigation and so on.

The entire work is organized into three important phases and they are image pre-processing, feature extraction and classification. As satellite images contain numerous features, this work intends to extract multiple features for accurate image classification. Initially, the satellite images are pre-processed with the help of median filter and the contrast of the satellite image is enhanced by employing Contrast Limited Adaptive Histogram Equalization (CLAHE). The feature extraction process is achieved by combining multiple features such as first order, Gray Level Co-occurrence Matrix (GLCM) and Lifting Wavelet (LWT) features to build the feature vector.

The classifier Support Vector Machine (SVM) is trained with the framed feature vector, such that the classifier can differentiate between various objects in the satellite image. The highlights of the proposed work are listed below.

- The contrast of the satellite image is enhanced by CLAHE in the pre-processing stage.
- The feature vector of the satellite image is created by combining different features such as first order, GLCM and LWT.
- Two levels of feature extraction detect fine features from the satellite images.
- Employment of SVM as the classifier to distinguish between various objects in the image.
- The proposed algorithm is observed to be accurate.

The remainder of the paper is organized as follows. Section II presents the review of literature with respect to classification of satellite images. The proposed approach is presented in a detailed fashion in section III. The performance of the proposed work is analyzed in section IV. Finally, the conclusions are drawn in section V.

## REVIEW OF LITERATURE

This section presents the related review of literature with respect to satellite image classification.

In [4], an unsupervised land cover classification scheme for multispectral satellite images is presented. The proposed scheme utilizes the concept of self-learning and cluster ensembles. The cluster ensembles deal with the iterative expectation-maximization (EM) algorithm, which generates the cluster attributes. The classifier being employed in this work is maximum likelihood classifier and is trained by the cluster attributes formed by EM algorithm. This classifier does not require any supervision. A satellite image classification system is presented in [5], which is based on morphological component analysis. The dictionary is constructed by utilizing independent component analysis. The morphological feature vectors are constructed by considering the texture and cartoon layers. The satellite images are classified by maximum likelihood approach.

An efficient unsupervised classification scheme is proposed for high resolution satellite images in [6]. This work can provide accurate segmentation and the number of segments are automatically set. The work proposed in [7] introduces a rule based system for satellite image classification, which is based on fuzzy logic. Additionally, genetic algorithm is employed to choose the optimal set of fuzzy rules to make the process simpler. The accuracy rates of this work is claimed to be better. A satellite image classification system that is based on Two-layer Sparse Coding (TSC) is presented in [8]. The TSC identifies the original neighbours of the images, without any training process. The satellite images are classified on the basis of TS coding coefficients.

In [9], an image classification system for multidimensional satellite images is proposed. The proposed work relies on the Gaussian Mixture Model (GMM) and the Bayesian approach. The GMM is employed for feature extraction and the Bayesian approach is to achieve classification. This work utilizes several techniques together to achieve better accuracy rates. The authors of [10] review the use of Support Vector Machine (SVM) in satellite image classification. For instance, the SVM based approaches such as active, semi-supervised SVM are studied and their performance over satellite images is reviewed.

A Convolutional Neural Network (CNN) based satellite image classification system is presented in [11]. This work proposes a two step training process, in which the initial step may involve several irrelevant data and so, the next step refines the data. The classification process is achieved by multiscale neuron module. In [12], a new ensemble based technique is proposed for image classification. The technique is named as ‘rotation random forest’, which is made possible by Kernel Principal Component Analysis (KPCA). The initial feature set is decomposed into several feature subsets, followed by which the KPCA is applied over each and every subset. The KPCA extracts statistical features and are clubbed together to train the Random Forest.

An unsupervised land cover classification system is proposed in [13]. This approach employs genetic algorithm with several metaheuristic algorithms. This work concludes that one in four satellite images is correctly classified. A multi-label classification scheme for satellite imagery is presented in [14]. In order to prove its capability, the same work is applied over hyperspectral satellite images also. A neuro-fuzzy based classification technique for classifying between the soil types is presented in [15]. The performance of this approach is compared against Radial Basis Function Network (RBNF), k-Nearest Neighbour (k-NN) and SVM. In [16], a phenology based classification technique that is based on SVM is presented. This work classifies between the croplands of Iraq.

Motivated by the above works, this paper aims to present a satellite image classification system for randomly selected images from Quickbird [17]. The proposed technique employs SVM as the classifier for the purpose of distinguishing between the land, vegetation and water sources. This paper extracts first order, GLCM features from the images. Additionally, the same set of features is extracted after the application of LWT. The feature vector is constructed by combining all these features and the SVM is trained. The proposed approach is elaborated in the following section.

## PROPOSED ALGORITHM

### *A. Outline of the Work*

The main intention of this research article is to present an accurate satellite image classification system, which relies on image pre-processing, feature extraction and classification phases. The image pre-processing phase processes the satellite image, so as to make it suitable for the forthcoming phases. This phase denoises and improves the contrast of satellite images. The median filter and CLAHE technique are utilized to eliminate unwanted information and enhance the contrast of satellite images respectively.

The pre-processed images are passed to the feature extraction phase, in which the first order, GLCM and LWT features. Initially, the first order features such as mean, Standard Deviation (SD), skewness and kurtosis are extracted from the image. GLCM features such as homogeneity and entropy are extracted. This is followed by the application of LWT and the same set of features is extracted from the approximation band of the images.

Finally, all the extracted set of features is combined together to form the feature vector. The SVM is trained with the constructed feature vector. In the testing phase, the image is pre-processed and the features are extracted from the input test image.

SVM classifies the soil, vegetation and water bodies of the satellite image, with the knowledge gained in the training phase. The performance of the classifier is analyzed by comparing the classified image and the ground truth image. The overall flow of the proposed work is presented in figure1. In figure 1, the dotted lines represent the training phase.

The reason for employing median filter for image denoising is that it preserves the edges, while removing unwanted information from the image. The CLAHE is a local contrast enhancement technique, which controls the noise amplification and gives the image a natural look. The first order features such as mean, standard deviation, skewness and kurtosis are extracted, as these features are rich with intensity information of an image.

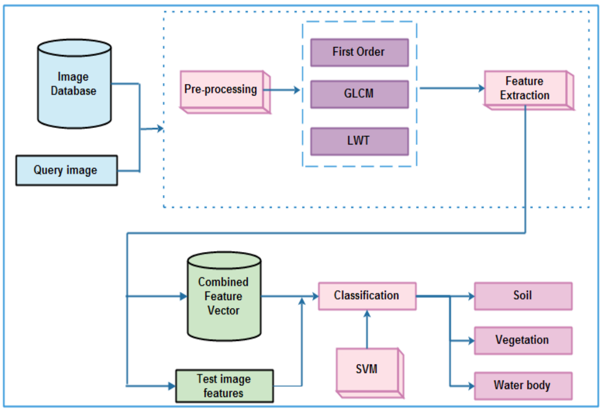


**Figure 1:** Overall view of the proposed approach

The GLCM features such as homogeneity and entropy are extracted, as they determine the local distribution of gray levels in the image. Additionally, the second level of feature extraction is carried out by applying LWT, as it performs well on noisy images. The same sets of statistical features are extracted from the LWT applied image. The feature vector is formed by combining all the extracted features and the SVM is trained. In the classification phase, the SVM strives to differentiate the soil, vegetation and water bodies.

### *B. Satellite Image Pre-processing*

Satellite image pre-processing is the preliminary step of any image processing activity. The main goal of this phase is to process the image in such a way that it is appropriate for the successive image processing activities. This work improves the image quality by employing median filter and CLAHE technique.

The basic idea of median filter is to remove the high frequency components from the satellite image. The main advantage of median filter is that it maintains the edge information and it performs window based pixel operation. The median filter is applied over all the pixels of an image size of the window is fixed as $11 \times 11$. The sample pre-processed images are shown in figure 2.

The pixel values of every window are set in ascending order and the median value is chosen for altering the image. The CLAHE technique intends to enhance the contrast of the satellite image and it improves the brightness level of an image. This makes the process of differentiating between several areas easier.

The advantages of CLAHE are simplicity and the protection of image from brightness saturation [18-20]. In fig.2, (a) denotes the input images and (b) denotes the pre-processed images. The next sub-section elaborates the process of bi-level feature extraction scheme.

*C. Bi-level Feature Extraction Scheme*

This work employs bi-level feature extraction technique, which extracts features in two ways. Initially, the texture features are extracted by statistical and GLCM feature extraction techniques. Again, the same sets of features are extracted from the images after the application of LWT. All the extracted features are combined together to form the feature vector. The following section explains the feature extraction process in detail.

*1) Statistical Feature Extraction*

The statistical texture features are beneficial for differentiating between multiple images. These local texture features reveal useful information about the intensity distribution of the images. This work considers the first order features such as mean, standard deviation, skewness and kurtosis.


**Figure 2:** Sample pre-processed images

Mean is the feature that calculates the average of the intensity distribution. Hence, the brightness level of an image can be determined by the mean. The greater the mean value, the brighter is the image and vice versa. The mean is computed by

$$\mu = \frac{1}{N_p} \sum_{r=1}^{m} \sum_{c=1}^{n} k[r,c] \quad (1)$$

Where $N_p$ is the total count of pixels of an image, $r$ is the row, $c$ is the column and $k[r,c]$ is the value of the corresponding pixel. Standard deviation is the next feature which represents the contrast of the gray level intensity of an image. Hence, the lower standard deviation indicates that the image is with lower contrast and is denoted by

$$\sigma = \sqrt{\frac{1}{N_p - 1} \sum_{r=1}^{m} \sum_{c=1}^{n} (k[r,c] - \mu)^2} \quad (2)$$

Skewness is the third feature, which denotes the skewed intensity. The intensity distribution with respect to mean is measured and the resultant value can either be positive or negative. The positive skew value indicates that more intensity values lie on the left side of the mean and vice versa. When the value of skewness is zero, then the intensity values are equally scattered on both sides of the mean. Skewness is computed by

$$\gamma = \frac{1}{(N_p - 1)\sigma^3} \sum_{r=1}^{m} \sum_{c=1}^{n} (k[r,c] - \mu)^3 \quad (3)$$

Kurtosis is the feature that measures the peak of intensity distribution around the mean value and it is denoted by the following equation.

$$\delta = \frac{1}{(N_p - 1)\sigma^4} \sum_{r=1}^{m} \sum_{c=1}^{n} (k[r,c] - \mu)^4 \quad (4)$$

This feature notifies about the data distribution with the sharp or blunt peak with respect to the mean. This step is followed by the extraction of GLCM features, as GLCM is the most famous statistical method for extracting texture features.

This work utilizes two most important features such as homogeneity and entropy. Homogeneity is the measure whose value is greater, when the gray level distribution is uniform and is denoted by

$$\tau = \frac{\sum_{r=1}^{m-1} \sum_{c=1}^{n-1} (k[r,c])}{1 + (r-c)^2} \quad (5)$$

Entropy is another important GLCM features, which denotes the information that has been lost by the image. Besides this, the amount of information that an image possess is measured.

$$\varphi = \sum_{r=1}^{m} \sum_{c=1}^{n} -k[r,c] * \log k[r,c] \quad (6)$$

After extracting these statistical texture features, the same set of features are again extracted from the LWT applied image. The second round of feature extraction with LWT is presented below.

*2) Feature Extraction on LWT Applied Image*

This work applies LWT, so as to have better feature sets. LWT is applied, as it is proven to safeguard the spectral properties of an image along with better denoising capability [21, 22]. LWT is proposed in 90's by Daubechies [23].

The LWT is composed of three main phases and they are split, prediction and update phase. This kind of wavelet is based on the dual orthogonal wavelet with enhanced dualization. The split phase intends to split an image and this splitting process is called as lazy wavelet transform. The images are divided into two groups and are named as odd and even groups. The splitting process can be represented as follows.

Let $im_k$ be the data applied with LWT, then $im_k$ is decomposed into odd and even sample group. The odd and even sample group are represented by $odd_{k+1}$ and $even_{k+1}$. In the prediction phase, the odd sample group is predicted with the help of the neighborhood even sample group. This phase introduces a new entity called prediction factor and is denoted by $P$. In this phase, a high pass coefficient or detail coefficient $hp_{k+1}$ is computed as prediction error, while handling the odd sample group. On the other hand, the prediction factor is utilized for even sample group and is represented by

$$hp_{k+1} = odd_{k+1} - P(even_{k+1}) \quad (7)$$

In the update phase, the approximation coefficient $ac_{k+1}$ is generated by updating the detail coefficient on the even sample group and is achieved by the update factor ($Up$). The update phase is denoted as follows.

$$ac_{k+1} = even_{k+1} + Up(hp_{k+1}) \quad (8)$$

The satellite images are applied with LWT and the approximate bands of the images are extracted for further processing. The above mentioned texture features are extracted from the approximate bands of the satellite images, as the approximation bands possess all the intensity information. The overall algorithm for the proposed approach is presented below.

*Overall algorithm*

*Input: satellite images;*

*Output: classified satellite images by soil, vegetation, water body*

*Begin*

*//Pre-processing*

*Denoise the image by median filter;*

*Enhance the contrast of image by CLAHE;*

*Store the pre-processed images;*

*//Feature extraction*

$E1$: *Extract first order features* $(\mu, \sigma, \gamma, \delta)$*;*

$E2$: *Extract GLCM features* $(\tau, \varphi)$*;*

*E3: Apply LWT over images;*

*Segregate the approximation band;*

*Extract E1 and E2;*

*Build feature vector (E1,E2,E3);*

*Save the feature vector;*

*//SVM classification*

*//Training*

*Train SVM with the feature vector;*

*//Testing*

*Input: Test image, number of classes (n)*

*Begin*

*Perform pre-processing and feature extraction;*

*Build feature vector;*

*Employ* $\frac{n(n-1)}{2}$ *SVMs;*

*For (1 to n classes and 1 to t objects)*

*Store SVM's decision;*

*Detect the class for an object with maximum votes;*

*Declare the object's class;*

*End;*

*End;*

Once the features of LWT applied images are extracted, the feature vector is formed by considering the first order, GLCM and LWT applied image features. The SVM is trained with the constructed feature vector and the process of classification is presented as follows.

*D. Satellite Image Classification by SVM*

SVM is the supervised classification algorithm that intends to classify between the objects by setting a boundary. However, binary SVM is not feasible for the works with multiple categories. In this case, multiclass SVM is employed. In this work, multiclass SVM is employed as the work considers three different classes such as soil, vegetation and water body.

This work differentiates between soil, vegetation and water body by incorporating $\frac{n(n-1)}{2}$ classifiers and the final decision of all these classifiers are taken into account. Finally, the regions are classified by max-voting policy [24]. Thus, all the different classes are processed simultaneously by solving the below given equation.

$$min_{nh,b,sv} \frac{1}{2} \sum_{y=1}^{q} nh_y^p nh_y + c \sum_{i=1}^{r} \sum_{y \neq s_i} sv_{i,y} \quad (9)$$

Here, $nh$ seems to be normal to the hyperplane, b is the bias, $sv$ is the slack variable, $i = 1,2, \ldots r$ are training samples and

$y$ is the count of classes. The conclusive decision is done by the following equation.

$$decn = max_y(w_y^p \beta(x_i) + b_y) \quad (10)$$

In this approach, all the classifiers are applied on every single pair of classes. Consider an object $obj$ that has to be differentiated to one of three different classes (say x,y,z) . This process is accomplished by applying all the classifiers over an image.

Whenever a classifier differentiates the object to be in class x, then the value of class x is incremented by 1. The final classification decision is taken on the basis of the maximum votes for the class. This way of classification ends up with accurate decision in a reasonable span of time. The following section analyses the performance of the proposed approach.

## RESULTS AND DISCUSSION

This work takes the images of the Aeugst am Albis of Switzerland into account for the purpose of image classification. The images being considered for this research lie between 47.268703 latitude and 8.491021 longitudes. The GPS coordinates of the image is 47º 16’7.3308” N and 8º 29’27.6756” E. This section analyses the performance of the proposed approach by varying the feature extraction and classification techniques in terms of accuracy, sensitivity and specificity. The proposed approach is tested by considering the satellite images downloaded from the quickbird site [17]. The experimentation is done in the matlab environment. This work trains and tests the system with 25 images each respectively. The sample classification results are shown in the figure 3.

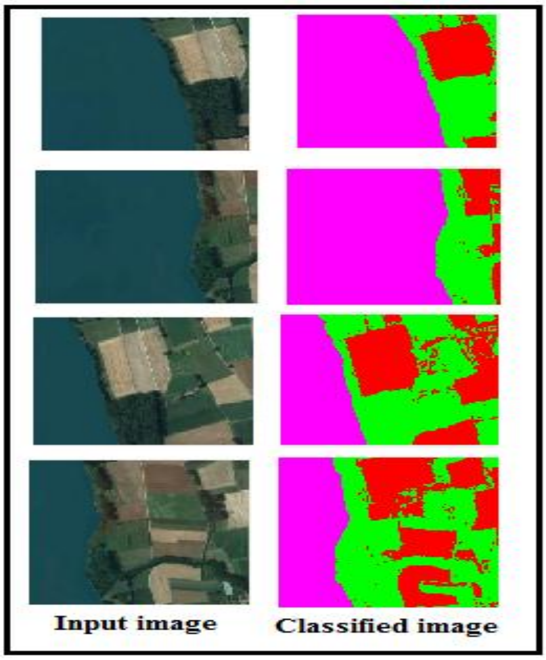


**Figure 3:** Sample classification results

Classification accuracy is the most important parameter for any classification algorithm. The efficiency of the classification depends on the effectiveness of the features being extracted. The accuracy of the classification algorithm is computed by the following equation.

$$ac_{rate} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (11)$$

In eqn. (11) TP and TN are the true positive and true negative rates respectively. Similarly, FP and FN are false positive and false negative rates respectively. Sensitivity and specificity are other important measures that could rate the performance of the classification algorithm.

Sensitivity is the measure which is the rate of correctly classified images to the sum of images that are correctly classified as positive and wrongly classified as negative. Specificity is measured by the ratio of the sum of images that are correctly classified as negative to the sum of images that are incorrectly classified as positive and correctly classified as negative. The sensitivity and specificity are represented as follows

$$sens_{rate} = \frac{TP}{TP+FN} \times 100 \quad (12)$$

$$spec_{rate} = \frac{TN}{FP+TN} \times 100 \quad (13)$$

TP is the count of images that are correctly classified with respect to the class and TN is the count of images that are correctly classified as these images do not belong to a particular class. FP is the count of images that are wrongly classified as these images belong to a particular class and FN are the count of images that are misclassified as the images do not belong to a specific class.

The accuracy, sensitivity and specificity are measured by varying the feature extraction techniques (with LWT, without LWT) and classifiers (k-NN, RVM and SVM). Relevance Vector Machine (RVM) is a machine learning approach and is based on Bayesian concept. However, the accuracy rates of RVM are lower than SVM [25]. The comparison analysis by varying feature extraction techniques is carried out by employing SVM as the classifier. The experimental results of the proposed approach are presented in Table 1.

**Table 1:** Comparative analysis by varying feature extraction and classification techniques

| Techniques Performance Measures | Comparison by varying Feature Extraction Techniques | | Comparison by varying Classification Techniques | | |
|---|---|---|---|---|---|
| | First Order + GLCM features | Proposed | k-NN | RVM | Proposed SVM |
| Accuracy | 97 | **99.8** | 72 | 92 | **99.4** |
| Sensitivity | 91.6 | **98.6** | 68 | 86 | **98.7** |
| Specificity | 93 | **99** | 66 | 90 | **99.2** |

In order to emphasize the effectiveness of LWT, this work compares the accuracy, sensitivity and specificity rates of the feature extraction techniques. The experimental results show that the LWT contributes a remarkable significance in the performance. A wide variation in the performance is observed in the absence of LWT. Thus, the employment of LWT is justified. The table presents the comparative analysis on different classifiers with respect to accuracy, sensitivity and specificity rates.

The classifiers take all the LWT, first order and GLCM features into account. The performance of SVM is compared with other analogous classifiers such as k-NN and Relevance Vector Machine (RVM). From the experimental results, the efficacy of the SVM is proven. Though the experimental outcome of RVM is comparable with SVM, SVM performs better. The maximum accuracy, sensitivity and specificity rates are achieved by SVM. From the experimental results, it is evident that the proposed satellite image classification algorithm performs better in terms of standard performance measures.

## CONCLUSION

This article presents a satellite image classification algorithm which relies on the texture features. Understanding that the satellite images contain rich texture properties, this work performs bi-level feature extraction. Initially, this work extracts first order texture features (mean, standard deviation, skewness, kurtosis), GLCM features (homogeneity, entropy). Subsequently, the satellite images are applied with LWT and the approximation band is pulled out. The same sets of features are extracted from the LWT applied satellite images and the feature vector is formed. Finally, SVM is employed as the classifier to distinguish between the soil, vegetation and water bodies. The performance of the proposed approach is observed to be satisfactory in terms of accuracy, sensitivity and specificity. In future, the performance of the satellite classification is planned to be analyzed by incorporating clustering technique.

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