Machine Learning Approach for Road-Line Extraction in Complex Urban Environments from High-Resolution Hyperspectral Image

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Abstract. Road network extraction and road line extraction from remote sensing images is still challenging task due to the complex structure of urban areas. The spectral response, design, shape, size, shadow, a contrast of roads, and other urban features are similar, which causes inaccurate results. The present paper investigates the asphalt road line extraction from high spatial-spectral resolution hyperspectral imagery. The implemented approach is based on a machine-learning algorithm, i.e., Support Vector Machines (SVM), structural information, and road line filtering. Road and non-road classification have been done using the SVM algorithm, generating a road map. In the second step, mathematical morphology was used to extract the road network with enhanced precision. Unwanted material has been removed using the granulometry approach. Finally, accurate and comprehensive road line extraction has been done by median filtering. The results have shown 85.13% correctness with 79.93% completeness of the implemented methodology. The experimental results are helpful for transportation analysis, traffic management, cartography, urban planning, and its management.

Keywords: Road-line extraction · Machine learning · Hyperspectral image · Mathematical morphology · Support vectors

1 Introduction

Road network extraction using remote sensing is essential in several applications such as transportation analysis, traffic management, urban planning, cartography, and updating the Geographic Information System (GIS), etc. [1–5]. The advancements in remote sensing imagery provide very high spatial and spectral information for road network extraction that can be used to modernize and preserve the GIS in real-time monitoring of

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numerous applications [1, 2]. Several studies have been done on road network extraction, including automatic road detection from remote sensing images. Most of the methods suggested by researchers for road extraction comprise one or more approaches, such as image classification or segmentation, edge detection and preserving, bridging and cleaning broken roads, and matching road templates [1, 3, 5].

Several studies have testified road network extraction using medium or high-resolution remote sensing images following various approaches. For instance, Ünsalan et al. [6] applied probabilistic and graph theoretical methods to detect road networks. They performed experiments on very high-resolution satellite and aerial image sets. The study [1] proposed the framework consisting of three aspects: generation of rod map using pixel-based method, filtering road networks by guided filter and shape feature method, and road center line extraction by merging multiscale Gabor filter and fast parallel thinning method. They used free remote sensing images and restored the discontinued road network. The work reported by [5] focuses on road detection systems using high-resolution IKONOS multispectral images. The performed approach was based on SVM and multiscale structural feature extraction. Das et al. [3] extracted salient features of roads from high-resolution multispectral satellite images using Probabilistic SVM and dominant singular measures. The research carried out by [4] proposed a new method for road network extraction via two remote sensing images using a DenseUNet model using limited parameters. However, the results obtained in their way are difficult to apply to the other issues in road network extraction. On the other hand, Shao et al. [2] have designed the challenging datasets from the GF-2 satellite for road surface and centerline extraction. In addition, multitask convolutional neural network models have been used to extract two tasks simultaneously.

However, road network and road line extraction remain challenging due to several similar urban structures like buildings, trees, vegetation, and the complexity of urban areas. Furthermore, road network extraction and its complete automation are complicated tasks that have not been addressed accurately over a complex and extensive set of remote sensing images. Moreover, the followed methodology varies from acquisition sensor to sensor and geo-location of the area. In this case, the researcher proposes different methods and sets several experimental parameters to obtain accurate results with sufficient accuracy.

The present study aims to implement a machine learning and image processing approach on high-resolution satellite images for asphalt road extraction in complex urban environments. The set objectives are: (1) Pre-processing of hyperspectral image, (2) Classification of road and non-road objects along with road map generation using SVM algorithm, (3) Extraction of road network from a classified image using morphological operations and granulometry approach, (4) Extraction of road line and smoothing of roads, (5) Results evaluation.

The paper is divided into five sections. This section introduces the background of the study, recent advancements, implemented approach, and set objectives. Section 2 briefs the used satellite data. The methodology is provided in Sect. 3, which includes pre-processing, classification, target detection, and extraction. Results and discussions are presented in Sect. 4 with achieved accuracy. Section 5 concludes the study with future scope.

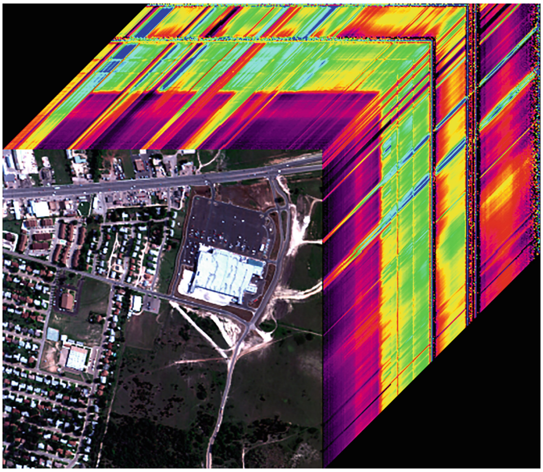

Fig. 1. Urban dataset false-color composite image with bands 47, 26, and 16 for the red, green, and blue wavelength, respectively.

2 Hyperspectral Image Data

In the present study, the hyperspectral digital collection experiment (HYDICE) dataset, Urban of Copperas Cove, Texas [7], has been used to perform the experiments. The HYDICE data consists of complex urban structures, which are used mainly to unmix urban features. There are 307 $\times$ 307 pixels, with a 2 $\times$ 2 m^2 area. This image's 210 spectral wavelength bands range from 400–2500 nm with a high spectral resolution of 10 nm [8]. Figure 1 shows the false composite color of the used image composed of bands 47, 26, and 16 for the red, green, and blue wavelengths.

3 The Methodology

The methodology implemented in the present study is shown in Fig. 2, which includes pre-processing, preparation of primary map using binary SVM classification, road network extraction using morphological operations, road line extraction using median filter, and preparation of the final map.

3.1 Pre-processing

The downloaded raw image has 210 spectral bands with unknown wavelengths and irrelevant values. Thus, firstly we set the wavelengths and FWHM units in nanometres and provided correct wavelength values for each band ranging from 400 nm to 2500 nm. The original HYDICE image has several dense water vapor and severely polluted atmosphere bands. In addition, this image is distorted by heavy Gaussian noise, deadlines, and strips. As a result, the water absorption and polluted atmosphere bands (1–4, 76, 87, 101–111, 136–153, and 198–210) have been eliminated, and the remaining 162 bands were used for further processing [8, 9].

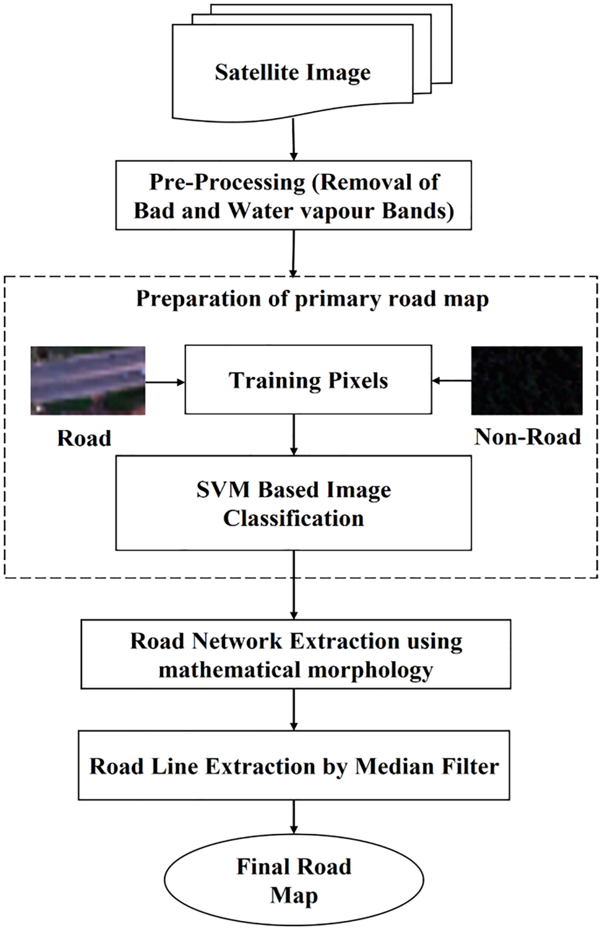

Fig. 2. Workflow of the implemented methodology.

3.2 SVM Based Image Classification

The hyperspectral image has several heterogeneous spectral variations and complex structures like grass, trees, metals, and roofs. These objects generate the asphalt road extraction task more challenging. Consequently, it is essential to identify the road network from high-resolution images using a classification approach. In the present study, we have used a pixel-based machine learning classification approach using SVM. The SVM is a statistical non-parametric method based on a supervised process [10] that requires very few training pixels to produce better accuracy. In addition, SVM works superior in the spectral feature change of the road material and intensity change [11]. The SVM uses the training pixels on the edges of class support vectors. However, the SVM has initially introduced for binary classification. Thus, the binary SVM approach is computed directly for roads and non-roads types in the present study. The SVM method based on Radial Basis Function (RBF) kernel [10, 12] has been used due to its high performance to classify the hyperspectral image into two classes, i.e., road and others using sufficient training pixels with Eq. (1).

$$(x) = \begin{cases} 1 & \textit{if x is a road class} \\ 0 & \textit{otherwise other class} \end{cases} \tag{1}$$

3.3 Road Network Extraction Using Mathematical Morphology

The mathematical morphology of opening and closing operators has been used in this study to extract the existing road network. The road maps (Fig. 3) classified using SVM contain noise and other features due to the spectral similarity of roads and other features such as buildings and asphalt areas. Thus, these similarity issues were resolved using morphological operations [13, 14] to enhance the accuracy of road network extraction. Mathematical morphology filtering is a non-linear method of processing digital images based on shape. Its primary goal is the quantification of geometrical structures. By using the opening operation, no shape noise is created. However, the granulometry approach extracted the shape or size distributions of the image features. Equations (2) and (3) are used to implement the opening and closing operations, respectively.

The opening of set X by structuring element Y, represented by $X \circ Y$, is an erosion followed by a dilation given in Eq. 2 [15, 16],

$$X \circ Y = (X \ominus Y) \oplus Y \tag{2}$$

The closing of set X by structuring element Y, represented by $X \cdot Y$, is a dilation followed by an erosion given in Eq. 3 [15, 16],

$$X \cdot Y = (X \oplus Y) \ominus Y \tag{3}$$

where $\ominus$ and $\oplus$ are the erosion and dilation, respectively.

3.4 Road Line Extraction by Median Filter

The extracted road network by morphological operations has several discontinuities due to obstruction affected by trees. Therefore, the median filter has been used to smooth an image while preserving better edge information and removing the outliers without diminishing the sharpness of the view. In addition, it eliminates the speckle noise caused in the previous step [17].

3.5 Performance Evaluation of Methodology

The performance evaluation of implemented methodology has been accessed using three widely accepted metrics such as correctness (A), completeness (B), and quality (C) [1]. Equations (4), (5), and (6) denotes correctness (A), completeness (B), and quality (C) metrics, respectively, and are used to evaluate the methodology.

$$A = \left(\frac{TP}{TP + FP} \right) * 100 \tag{4}$$

$$B = \left(\frac{TP}{TP + FN}\right) * 100 \quad (5)$$

$$C = \left(\frac{TP}{TP + FP + FN}\right) * 100 \quad (6)$$

where TP stands for true positive, FP and FN stand for false positive and negative, respectively.

4 Results and Discussion

The pre-processed hyperspectral image has been used to perform different methodology. The efficiency of the road extraction method has been assessed using ground truth data provided by [8]. It contains an urban hyperspectral image and ground truth of 6 pure classes. The image's 903 and 657 training pixels were used to classify road and other features, respectively. The RBF kernel of the SVM method has been utilized to generate an initial road map. The set parameters of the RBF kernel function were penalty parameters C (100), gamma value (0.1), pyramid level (1), pyramid reclassification threshold (0.90), and classification probability threshold (0.1).

The SVM model has been trained using optimized variables, and the classification map is prepared. The classification map generated by the SVM method is illustrated in Fig. 3, representing classified road networks and non-road classes. The classified road map (Fig. 3) using the SVM method clearly shows other features like roofs and specks of dirt due to their spectral similarities. It is observed from Fig. 3; the map has produced some insignificant outcomes. Furthermore, this road map (Fig. 3) also contains some noises. Thus, the non-road features and shape noises were eliminated using the prior road map's morphological operations and granulometry approach.

Figure 4 shows extracted road network performing morphological operations. It is observed from Fig. 4 that the road network has been successfully extracted, eliminating the noises and spectral similarities. However, Fig. 4 contains building structures along with a road network. The broken road network has been repaired to allocate a precise road network. These discontinued roads have been repaired by median filtering. The 3×3 kernel of median filtering [17] has been used to smooth roads while removing the roadside building structures. The road extracted by median filtering is shown in Fig. 5. It is confirmed by the obtained results (Fig. 5) that the road line has been pulled accurately by the implemented methodology. The extracted road line is evaluated using provided ground truth data. The computed methodologies' performance is evaluated by completeness, correctness, and quality [1] implemented by true positive, false positive, and false negative. The implemented methodology's completeness, correctness, and quality were 79.93, 85.13, and 67.49%, respectively.

The implemented methodology's efficiency is satisfactory compared to recent studies [1, 2].

Fig. 3. Classified image using pixel-based SVM method.

Fig. 4. Image after road network extraction by morphology.

Fig. 5. Image after road line extraction by median filtering.

5 Conclusions

This work uses a composite structure of a machine learning algorithm for pixel-based classification, morphological operations, and median filtering to extract the asphalt road network and road lines from the high-resolution hyperspectral image. This work's novelty consists of using spatial and spectral information for road line extraction using the SVM method and fusion of different information. The experimental results are assessed using three evaluation methods: completeness, correctness, and quality with satisfactory accuracy. The implemented methodology eliminates road line issues like reconstruction of disconnected roads and extraction of the correct and smooth road lines as confirmed by the experimented results. More satellite images will be used in the future, results will be compared with standard literature, and road topology will be analyzed for real-time applications.

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