Automatic Road Feature Extraction using MRF from LANDSAT-8 OLI Images

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***Abstract*—Road detection from the remote sensing images is essential in automating map updation and town planning applications. In this paper, we propose an index based road feature extraction from OLI images using the Markov Random Fields (MRF) model. The proposed index is named as Normalized Difference Asphalt Road Index (NDARI) with a combination of two indices. These two indices are derived based on the reflectance differences of asphalt in the NIR, SWIR1 and Blue bands of OLI Images. They produce the low values for the asphalt features compared to other features in the image and results in roads that are darker than other features. To highlight the road features in the NDARI images, Mathematical Morphology (MM) i.e., Bot-Hat transform is used. Finally, image segmentation is done by using the MRF model. The parameters (mean and variance) are estimated by the Maximum-Likelihood Estimation (MLE) and Expectation-Maximization (EM) for each class label. The methodology is performed on the LANDSAT-8 OLI images and the results are presented, it is observed that the proposed method is producing the satisfactory results.**

***Index Terms*—Road Index, Markov Random Fields, OLI, Expectation and Maximization**

I. INTRODUCTION

Automatic Road feature extraction from the Remote Sensing (RS) images is a crucial task for automating several types of applications. It can be used in the map updation at regular intervals, town planning and monitoring the disasters. The main objective of the paper is detection of major roads from the LANDSAT-8 OLI data, with road widths greater than 25 meters. For monitoring and updation purposes, the satellite data needs to be acquired at shorter revisit and larger swath with reasonable spatial resolution, OLI sensor data is meeting these requirements with a spatial resolution of 15 meters. The road feature extraction from High Resolution (HR) images is a critical task due to increased complexity in the form of buildings, trees and their shadows, revisit time (Temporal Resolution) of the satellite etc. Conversely, in Low Resolution (LR) images major roads are mostly curvilinear, this will suffice LR images for the detection of major roads.

OLI has 12 bands, out of which 9 bands are multi-spectral bands with the spatial resolution of 30 meters and one Panchromatic band with the spatial resolution of 15 meters. The remaining two bands are Thermal Infra Red (TIR) with spatial resolution of 100 meters.

The rest of the paper is organized as follows, the literature work is presented in Section-II, the proposed index is given in Section-III, and the obtained results with analysis are presented in Sectin-IV.

II. LITERATURE SURVEY

In the literature, the researchers have proposed various methods for road feature extraction from RS images. Das et al. [1] presented an analysis on the road extraction using different methodologies. Many of the methods are focused on the algorithms which are based on single band or RGB bands. RS images have the multi-spectral bands in HR and LR sensor images. The multi-spectral bands are being used in various algorithms for feature identification as indices, for e.g., vegetation (Normalize Difference Vegetation Index (NDVI)), water (Normalize Difference Water Index (NDWI)) [2], [3] and built-up (Normalize Difference Built-up Index (NDBI)) etc. These indices are made on the basis that, a feature will have highest reflectance in atleast one band and a lowest reflectance in a particular band. Herald [4] and R.D.Garg [5] are presented their individual analysis on the characteristics of the asphalt in various conditions. K shahi et al. [6] presented a Road Extraction Index (REI) for the WorldView-2 images. From the research analysis carried out, we propose an index NDARI for road identification from OLI images.

In digital image processing, segmentation aims to cluster the homogeneous regions and is one of the widely used technique for pattern recognition, feature extraction etc. Various segmentation techniques have been proposed in the literature. Thresholding method is extensively used method in image processing like Otsu [7] for binary class segmentation, other methods like Region Growing, clustering [8] based approaches for binary and multi-class segmentation.

To segment the road feature from the proposed indices, we used the Markov Random Fields (MRF) [9]. This is a proven method and is being used extensively in several image processing applications such as image segmentation [10]- [13], classification [15], restoration and smoothing [10].

In this paper, we are using the MRF model for the segmentation of the Normalized Difference Asphalt Road Index (NDARI) image when there is no prior information available about the model parameters. The parameters are estimated

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by Maximum-Likelihood Estimation (MLE) and Expectation-Maximization (EM) methods [11] for each class label. The label image is generated automatically (maximum possible labels) by using the simple threshold on the NDARI image.

III. Proposed Index and Methodology

One of the successful and widely used method of feature extraction from RS images is normalized difference index methods like NDVI, NDWI, NDBI etc [14]. In this paper, we are proposing an index for the road feature extraction from the RS images based on the asphalt reflectance in all the bands. The roads are built with the different material combination and has specific signature at different bands of wavelength. Most of the Asphalt roads are made with mix of gravel, tar (asphalt) and some form of carbon type material. In [4] given the analysis on the different types of roads and their reflectance variations with age.

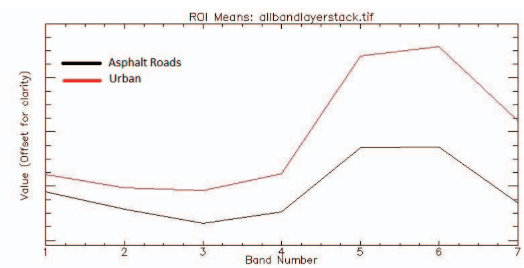


Fig. 1. Spectral Profile of Asphalt and Urban features

According to the analysis of Herald et al., the insitu reflectance values of the roads are observed as high in the NIR and SWIR region. It is observed that, asphalt road has very high reflectance and is matching with the response of bands like NIR (B5) and SWIR1 (B6) of OLI Images [3]. In blue band (B2), asphalt road has very low reflectance. The spectral profile of asphalt and urban areas of OLI sensor from all the bands of image is shown in Fig-1. Theoretically, the image spectral variation of asphalt and urban follows the same trend. From this we made two indices namely, Normalized Difference Road Index1 (NDRI1) and Normalized Difference Road Index2 (NDRI2). The proposed indices are mathematically given in eq.(1) and eq.(2).

$$\text{NDRI1} = \frac{B5 - B2}{B5 + B2} \tag{1}$$

and

$$\text{NDRI2} = \frac{B6 - B2}{B6 + B2} \tag{2}$$

The proposed indices are combinely named as Normalized Difference Asphalt Road Index (NDARI). NDARI is derived based on the slight spectral variation of asphalt from NIR to SWIR1 band ranges.

If NDRI1 alone is used thin roads are not getting detected and major roads are getting extracted, NDRI2 is able to extract the missed out remaining thin roads from NDRI1. NDRI2 is able to extract thin as well as major roads, but misses out the urban area thin roads due to its property of SWIR1 is having high reflectance for built-up area. Hence, By using the indices NDRI1 $\&$ NDRI2 together we could extract all the roads which otherwise were not possible by using NDRI1 or NDRI2 alone acting independently.

All the images or bands mentioned in paper are Top Of Atmosphere (TOA) corrected images [3]. By using NDARI index, roads alone were extracted by suppressing the remaining urban features.

A. MRF-MAP

The probability distribution of MRF model is calculated based on the information of the neighboring pixels of an image. This is expressed by the potential function of single pixels and the interactions in the group of pixels in relevant neighborhoods. This characteristic feature of MRF makes it ideal in image segmentation and specifically for pattern recognition applications. MRF results are unaffected by noise in the image. In LR-RS images the radiometric relation between the pixels of the features has wide variation. For feature detection like road features, the spatial resolution of the data used is twice that of the feature width in barren areas and four times in urban areas with differentiation from the other features. NDRI indices generate the fine details of roads and it leads to segment the images effectively. Here, the input image is a normalized image (i.e., NDRI1 or NDRI2) which is used as variable X (Bot-hat of NDRI) in the eq.(3). We need to find the absent label's $\hat{Y}$ of image (X) with the training samples or labels of Y. According to Maximum A Posteriori (MAP) criterion.,

$$\hat{Y} = \arg\max_{Y}\{P(X|Y,\mu,\sigma)P(Y)\} \tag{3}$$

where, P(Y) is a prior probability of the class and $P(X|Y)$ is the joint likelihood probability of observation. The Prior probability [10] is

$$p(x) = \frac{1}{Z}exp(-U(x)) \tag{4}$$

where Z is a normalizing constant. The MAP solution is obtained by minimizing the posterior energy function. The mathematical expression is

$$\hat{Y} = \arg\min_{Y}\{U(X|Y) + U(Y)\} \tag{5}$$

From the eq.(5), we can observe that the combination of the MAP technique with the MRF modeling makes the classification function.This function is identical to the total energy minimization. Hence, the iterative minimization gives optimized solutions. One of the widely used method in minimization problem is Iterative Conditional Models (ICM) [16] which finds the MRF-MAP Solution.The ICM algorithm gives efficient optimization solution for MRF-MAP estimates [17] and it converges to best local minima of the energy function.

Hence, it solved the global optimization problem p(x) by an iterative local optimization.

The model parameters mean μ and variance σ are unknown and estimated by using the EM algorithm and MLE by model fitting.

B. Parameter Estimation

The Probability Density Function (PDF) of multi variate gaussian distribution is

$$\mathcal{N}(x|\mu,\sigma) = \frac{1}{(2\pi|\sigma|)^{1/2}} exp\{-\frac{1}{2}(x-\mu)^T\sigma^{-1}(x-\mu)\} \quad (6)$$

The parameters i.e., mean (μ) and variance (σ) are estimated by using MLE of the texture.

$$\mu_k = \frac{1}{|S|}\sum_{s\epsilon S_i} f_s \quad (7)$$

$$\sigma_k = \sqrt{\frac{1}{|S_k|}\sum_{s\epsilon S_i}(f_s-\mu_k)^2} \quad (8)$$

where, S_k represents the number of pixels within the given area, $|S_k|$ represents the total number of pixels, f_s are values of pixels.

The initial parameters are predicted by using the Otsu method. It finds the initial values by maximizing the interclass and minimizing the intraclass variance. The mean and variance of each class are used as the initializing values for EM algorithm for estimating the final values. It is a generalized method used in incomplete data sets to find out MLE.

EM algorithm is an iterative scheme for finding a solution to the maximum likelihood problem. It mainly contains:

1) **Initialize** Initialize the parameters: number of classes (k), μ_k and σ_k,
2) **E-step** Evaluate the responsibilities using the current parameter values.

$$\gamma(z_{nk}) = \frac{\mathcal{N}(x_n|\mu_k,\sigma_k)}{\Sigma_{k=1}^{K}\mathcal{N}(x_n|\mu_k,\sigma_k)} \quad (9)$$

3) **M-step** Re-estimate the parameters using the current responsibilities.

$$\begin{aligned} \mu_k^{new} &= \frac{1}{N_k}\Sigma_{n=1}^{N}\gamma(z_{nk})x_n \\ \sigma_k^{new} &= \frac{1}{N_k}\gamma_k(z_{nk})(x_n-\mu_k)(x_n-\mu_k)^T \end{aligned} \quad (10)$$

4) **Likelihood** Recalculate the log likelihood function to see if it converges, if not, go to step 2 again. If X is a random variable and φ is a convex function. Then $\varphi(E[X]) \leq E[\varphi(X)]$.

The flow chart of the algorithm for the proposed methodology is presented in Fig.2. This method is performed on the two indices as given in eq.(1) and eq.(2). The results of individual indices are added to get the best results.

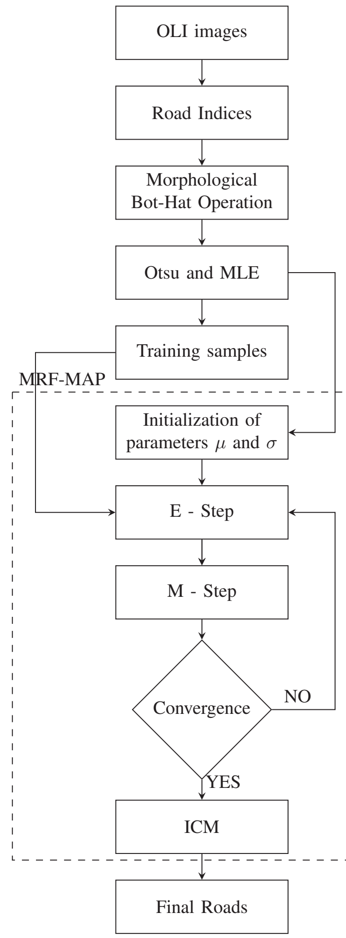


Fig. 2. Flow chart of Road extraction using MRF-MAP on Road Index

IV. Results and Analysis

The major roads are extracted by using the proposed methodology on OLI images covering the area of Hyderabad, India. The experimental results are presented by the proposed method on the TOA corrected images derived from L1TP (Level 1 Terrain Precision) products of OLI. The Hyderabad scene contains the large width roads like Outer Ring Road (ORR) (greater than 45 meters), major roads like National Highways (NH) and Rajiv Gandhi International Airport (RGIA) which are shown in Fig.3(a), Fig.4(a) and Fig.5(a). Using the proposed NDARI index and methodology, the major roads were extracted, by separating fine spatial details from the other features like barren lands, vegetation and buildings. Usage of the NDARI provided the combined results of NDRI1 and NDRI2 where the missing roads in NDRI1 were extracted in NDRI2. The experimental results with corresponding original images are shown in Fig.3, Fig.4 and Fig.5.

In Fig.3(a) is a sub-scene of Hyderabad which is covering

RGIA, ORR and NH-44, the roads whose width is greater than 25 meters and few roads which are less than this width are also extracted. The roads are extracted by NDRI1 and NDRI2 are shown in Fig.3(b) and Fig.3(c) respectively. These two results are added to get more roads is shown in Fig.3(d). It was also observed, that there are few gaps in the roads for the given image mainly due to road width being lesser ($\leq$ 20 m) and obstruction of vegetation.

The images shown in Fig.4(a) is a sub-scene of Hyderabad which is covering ORR, NH-65 and state highway-19. By using the NDARI indices the major roads like NH and ORR are efficiently extracted and are presented in the Fig.4(b), (c) and (d). It is observed that wherever the urban areas present with dense network of buildings there are gaps in between the roads, caused due to high reflectance of buildings in the SWIR band than asphalt, this can also be observed in Fig.3.

The usage of these two indices are demonstrated in Fig.3, 4 & 5. The roads are extracted by using the indices NDRI1 and NDRI2 are shown in Fig.3(b), 4(b) & 5(b) and Fig.3(c), 4(c) &5(c) respectively. Some of the roads missed in extraction using one index is recovered by the usage of the other index.

The area covered with the small road through a village which is Pirawa tahsil, Rajastan state, is taken as a case study with the minor road width is shown in Fig.7. From the result, NDARI is able extract the minor roads also where the conditions are like barren land around the roads. From the experimental results, it can be observed that, the roads like ORR and NH are extracted efficiently, except where the vegetation, dense network of buildings exists besides the roads. Hence, the proposed index is efficient index for extraction of major roads (with the road width of more than 25 meters) and better than the other methods in-terms of speed.

The gaps in between the extracted roads is resulted due to the road width being less than spatial resolution of the data being used i.e.,15 meters. The reference roads are drawn at 1:50,000 scale on the corresponding OLI images. The length (roundoff values) and accuracy of extraction of roads [22] from the OLI images are given in Table-I, II & III.

Table-I gives the lengths of the extracted roads from indices NDRI1 & NDRI2 with respect to the reference along with the common roads present in both indices. From this, we observe that, the road lengths obtained using individual indices are almost equal and the roads that were not detected using one index were got detected in another index. By combining the results of the two indices the roads were obtained whose length is higher than that can be obtained using individual. This can be observed from Table-I and Table-II results with accuracies obtained in Table-III. From Table-III, we observe that, if the roads other than NH are present, then the accuracy decreases.

The small gap filling is done with Morphological operations like dilation, erosion, opening and closing are shown in Fig.6. The remaining large gaps in the images by filling method is taken as the future work.

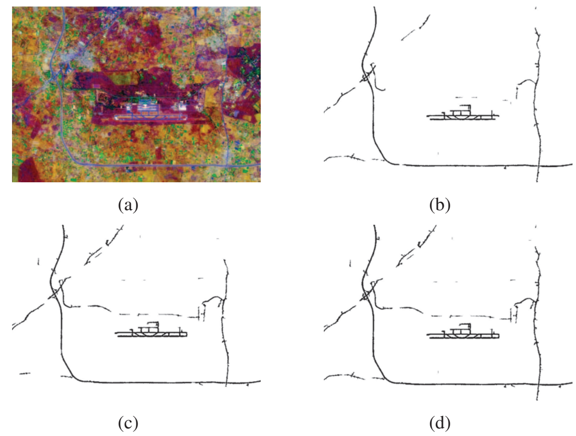


Fig. 3. (a) B762, OLI, RGIA Airport and ORR are sub scenes of Hyderabad, India (b) NDRI1, (c) NDRI2, (f) NDARI (combined)

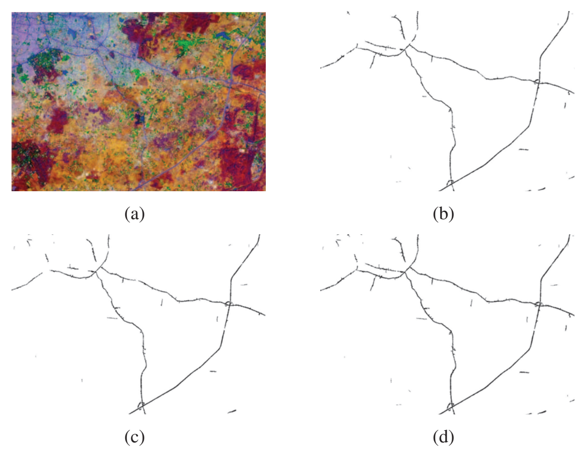


Fig. 4. (a)B762, NH65 and ORR are sub scenes of Hyderabad, India (b) NDRI1, (c) NDRI2, (f) NDARI (combined)

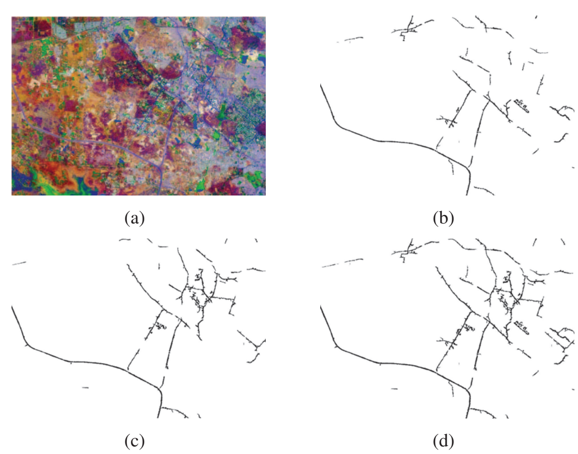
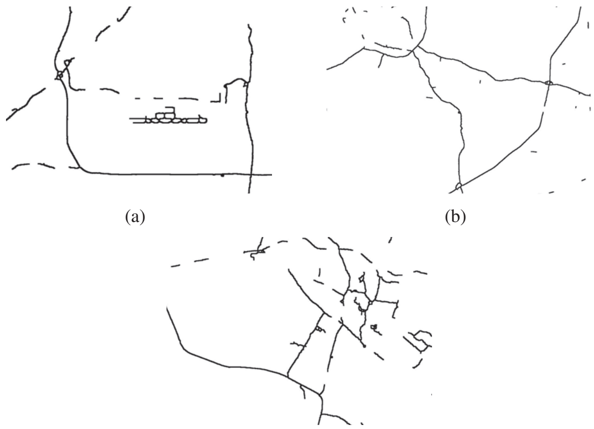
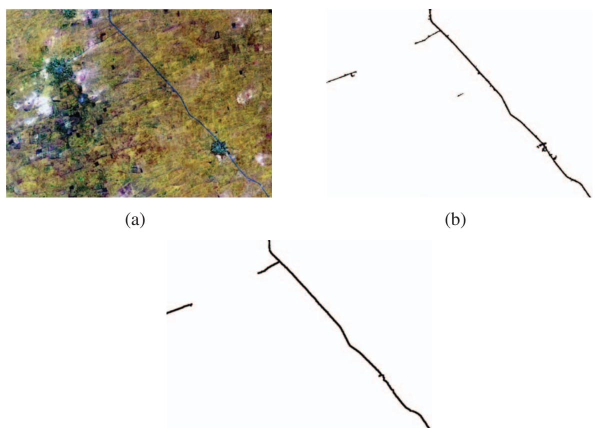


Fig. 5. (a) B762, Gachibowli ORR are sub scenes of Hyderabad, India (b) NDRI1, (c) NDRI2, (f) NDARI (combined)



(a) (b) (c)

Fig. 6. Smoothed by MM operations (a) of 3-(d) (b) of 4-(d) (c) of 5-(d)



(a) (b) (c)

Fig. 7. (a) Pirawa, Rajastan, B762 (b) Result of NDARI (c) Smoothed by MM operations

TABLE I
EXTRACTED LENGTHS OF ROADS (NDRI1 & NDRI2) IN KM

Fig. No.	Reference	NDRI1	NDRI2	Common roads
3	64	52	56	49
4	81	69	71	65
5	103	63	67	41

TABLE II
LENGTHS OF ROADS (NDARI) IN KM

Fig. No.	Reference	NDARI
3	64	61
4	81	75
5	103	89

TABLE III
ACCURACY OF NDARI

Fig. No.	completeness	correctness	Accuracy
3	90.62	95.51	86.95
4	87.71	94.69	83.60
5	80.76	94.38	77.06

V. CONCLUSION

In this paper, NDARI index is proposed for an automatic extraction of roads from the OLI multi-spectral images by using the NIR, SWIR1 and Blue bands. The NDARI (combination of NDRI1 & NDRI2) is proposed based on the spectral properties of asphalt. In NDARI images, the roads have low index values. Hence, by using the optimal threshold the roads can be extracted. To get more and efficient extraction of roads from the index, Bot-Hat transform was used on the indexed image to elevate the roads. Finally, the segmentation for road extraction is done by the MRF-MAP with EM and MLE algorithm. The proposed method is producing the satisfactory results as shown in section-IV and helps in roads digitization in-terms of time and cost. The gaps are observed in the extracted roads, are due to the insufficient road width, trees beside of roads and buildings.

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