IMPROVED ROAD NETWORK EXTRACTION BY SUPER-RESOLUTION MAPPING OF HYPERION IMAGE DATA

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ABSTRACT: This paper is concerned with the development of super resolution mapping approaches to extract the road network from a moderate resolution hyperspectral (Hyperion) image data. Super-resolution mapping is a technique which allows classification and mapping from coarse resolution images at the sub-pixel scale. In this work, the potential of Linear Spectral Unmixing and Support Vector Machine as inputs for Hopfield Neural Network based super resolution mapping. Further, integration of SVM as a soft-classified input to the SRM proved to be better than linear spectral unmixing (LSU) as soft classification input. The probability image obtained from support vector machine is used as an input for super resolution mapping designed on Hopfield Neural Network (HNN). For the evaluation of the technique, road segments are mapped using the Hyperion image (30m resolution and 242 bands) of Pondicherry city, south India. Producer's accuracy of the road class is 97.26% and user's accuracy is 91.03%. SRM with SVM as an input has achieved completeness of 0.594 and correctness of 0.863. The results proved that SVM as a soft classified input to the HNN based SRM is efficient and it results in overall accuracy of 92.97% for road network extraction from 30 m resolution image.

1. INTRODUCTION

The development of infrastructure such as a road network is one of the main tasks of the developing countries. With improvisation of road network through renovation and newly laid roads, it is pertinent to have updated road maps. Conventionally, road maps have been prepared by surveying (He and Orvets, 2000; Psarinos et al, 2001), using aerial photographs (Gruen and Li, 1995; Doucette et al, 1999), filters (Gecen and Sarp, 2008; Mena and Malpica, 2005) fusion (Lisini et al, 2006; Jin and Davis, 2005) and per-pixel classification (Fauvel et al, 2008, Sunil et al 2004, Song and Civco, 2004) techniques. These techniques have limitations such as: omission of details during survey, omission of details due to coarse medium resolution satellite images and omission of details of mixed pixel in the boundary of the features in high resolution images. To overcome these issues, this paper applies the super resolution technique as a method to extract road networks from a 30m resolution image.

Generally, the fraction image from linear spectral unmixing is provided as the input for the super-resolution classification (Atkinson, 1997; Tatem et al, 2002). In this work, the Hopfield Neural Network technique of super resolution mapping takes input from SVM. Evaluation of the performance of the super resolution mapping is carried out by conducting an experiment on road mapping application.

2. SUPER RESOLUTION MAPPING

Per-pixel classification of satellite image assumes only one class per pixel. This does not apply to mixed pixels. Sub-pixel classification computes the abundance of a class or material within a pixel but fails to account for the spatial distribution of the class proportion within a pixel. Super-resolution mapping is a technique which allows mapping at the sub-pixel scale. Several super-resolution mapping techniques have been proposed such as spatial dependence maximization (Atkinson, 1997), sub-pixel per-classification (Aplin and Atkinson, 2001), Hopfield neural network (Tatem et al., 2002), genetic algorithms (Mertens et al., 2003) and two-point histogram optimization (Atkinson, 2008).With super resolution mapping, this pixel will be subdivided, where every sub-pixel can be assigned its own class. This will result in an image with a higher spatial resolution than the one obtained from the per-pixel and sub-pixel approach, but mathematical optimization has to be done, which will give a result with better efficiency than other approaches. In this work involving the Hyperion image (30m resolution), a single pixel of the image is sub-divided into 25 pixels and the classes are assigned to each pixel based on the fraction image and optimized through Hopfield Neural Network.

Hopfield neural network is a feed-forward neural network, each neuron is modeled using an input and a sigmoidal activation function. It is a fully connected recurrent network. The Hopfield network can be used for energy minimization problems if the weights and biases are arranged such that they describe an energy function, with the minimum of energy occurring at the stable state of the network. The illustration for the super resolution mapping approach is given in Figure 1. Each pixel in the input image to the neural network is to be processed by a set of 5 X 5 (25) neurons. The network for each pixel processing is constructed with 25 neurons since a zoom factor of 5 is adopted.

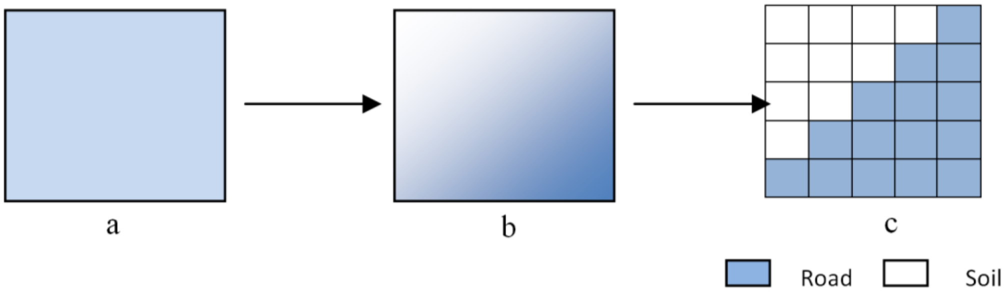


Figure 1. Illustration of Super-resolution mapping for a pixel containing both soil and road. a) a pixel representing a mixed pixel containing both soil and road. b) Soft classification output which produces a fuzzified results c) Super resolution output delineating the boundary between two classes

3. SUPPORT VECTOR MACHINE INPUTS FOR SRM

SVM is a statistical learning theory and non-parametric classification method that provides good classification results from the complex and noisy data. It uses optimal algorithms to locate best boundary between classes in feature space (Huang et al, 2002). The boundary is called separating hyperplane and has maximum margin from both classes (Vapnik and Cortes, 1995). The data points closest to the hyperplane are called support vectors. SVM has the ability to work with high dimensional feature space by applying kernel function (Karatzoglou et al, 2006). If data are non-linearly separable, SVM algorithm that explained in the previous sections cannot be applied for SVM classification. To solve the problem of nonlinear separability, input values transform to higher dimensional feature space H with the function Φ (Vapnik and Cortes, 1995).

$$R^k \rightarrow H, x_i \rightarrow \Phi(x_i) \tag{1}$$

As the dataset x_i is transformed to higher dimensional space and moreover working with $k(x_i, x_j) = e^{-\gamma\|x_i - x_j\|^2}$ If the equation of hyperplane is f(x) then distance of data x_i from the hyperplane is:

$$\boldsymbol{Distance}(x_i) = \frac{\boldsymbol{f}(x_i)}{\sqrt{\|\boldsymbol{w}\|^2}} \tag{2}$$

where w is the weight of hyperplane.

4. STUDY AREA

Pondicherry is an Indian union territory in south India. It is an urban agglomeration and municipality. It is endowed with excellent infrastructural facilities on par with the best available in the country. A network of all-weather metalled roads connecting every village exists in the territory. Pondicherry has a road length of 2552 km, the highest in the country. A part of this city with excellent planning is considered for the road mapping from super resolution methods. The specific area of the heritage town in Pondicherry is used in this study (Figure 2).

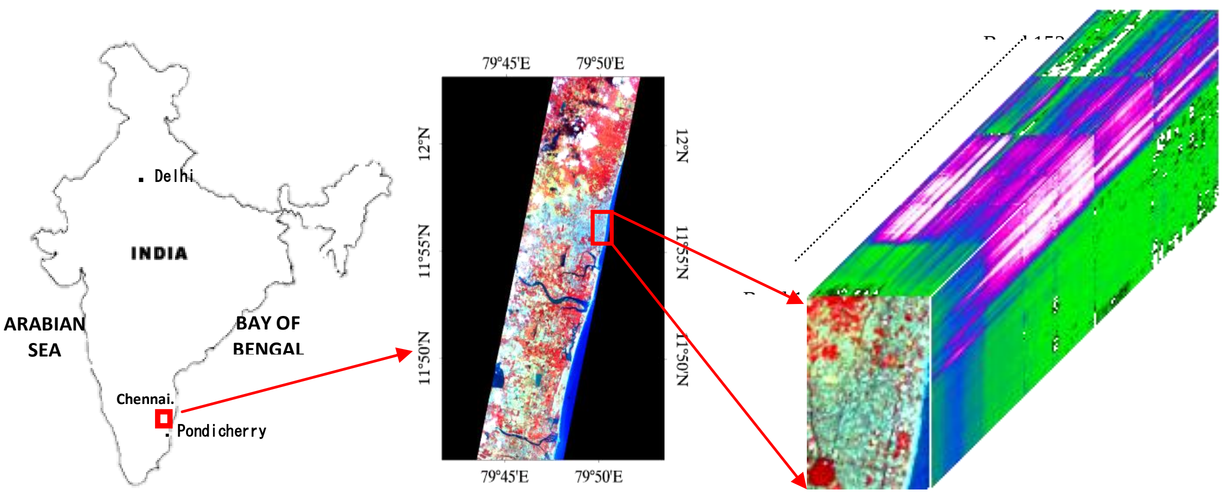


Figure 2. (a) Location of Pondicherry city, southern India and (b) Hyperion false-color composite image of the R (b55), G (b33), B (b15), and its hypercube. *Note: Scene centre co-ordinates:11˚56'12.21" N 79˚49'50.26"E*

5. METHODOLOGY AND IMAGE DATA USED

The methodology adopted for this study is given in the Figure 3. It involves applying SVM as an input for super-resolution mapping on the radiometrically corrected Hyperion data.

The hyperspectral data of EO1 Hyperion for super resolution classification approach with as an input for support vector machine used in this work. Hyperion has a spatial resolution of 30m with 220 bands. The sensor specification is given in Table 1. The use of hyperspectral image with narrow bands provide much information on the spectral characteristics of the land cover feature than the multispectral image with bands of broad wavelength range. Hyperspectral data result in classification efficiency due to the use of spectral seperability among the land cover classes (say soil, vegetation, road, buildings and water).

To obtain accurate and reliable results, atmospheric correction must be carried out for Hyperion data. There are many atmospheric correction algorithms. In this study, the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) atmospheric correction is applied for atmospheric correction of Hyperion data. After applying FLAASH, the bad bands are removed which has low detector-response (Gautam et al, 2012). Finally, 152 numbers of bands were chosen for this study on classification.

Table.1 Sensor specification of Hyperion

Parameters	Hyperion
Spectral Range	0.4-2.5μm
Spatial Resolution	30m
Swath Width	7.5Km
Spectral Resolution	10nm
Spatial Coverage	Continuous
Total number of bands	220
Date of Acquisition of image	9th February, 2009

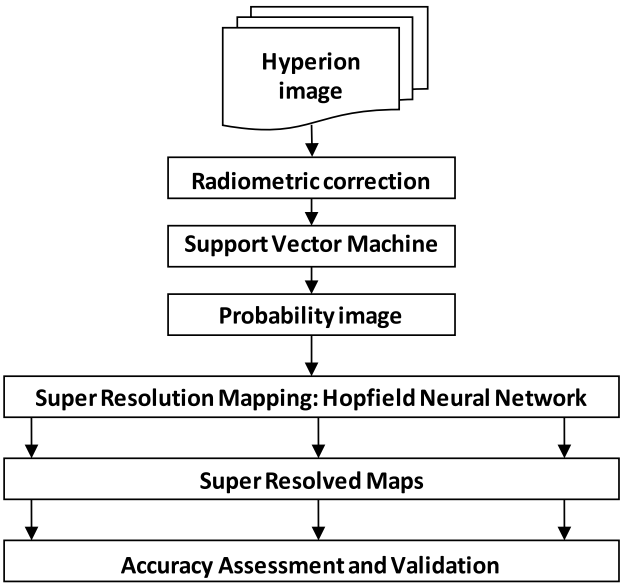


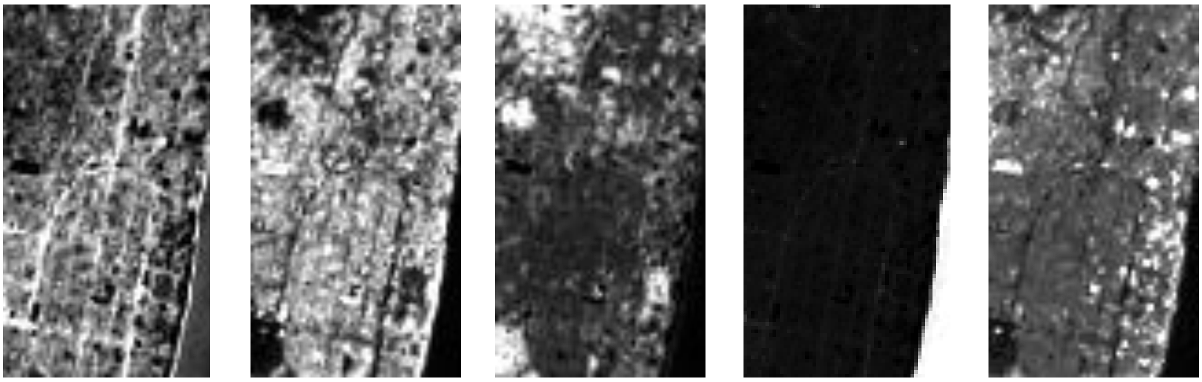
Figure 3. Flowchart depicting the methodology adopted in the study

6. RESULTS AND DISCUSSIONS

6.1. Road network extraction from SVM as input to super resolution mapping

Close examination of the road pixels in the false colour composite shows either grayish blue or whitish blue coloured pixels, which are certainly mixed pixels. There pixels may partially contain road, while the remaining components within the pixel may be soil or building. This mixed pixel is due to the fact that a road pixel cannot be represented in a pixel because often road is associated with tree and buildings nearby.

Though HNN based super-resolution algorithm helps in optimizing the distribution of classes within the sub-pixels, the soft classification input plays major role in efficiency of the output. The results of SVM incorporated with HNN based SRM proves to provide better results when compared to the other two techniques. SVM is able to consider more than three end-member pixels for classification. The road probability image and the building probability image precisely differ from the water probability image and the soil probability image respectively (Figure 4). This issue of confusion between the classes has been overcome by the SVM as an input.



a. b. c. d. e.

Figure 4. Probability images from SVM methods: (a) Road probability image **(b)** Buildings probability image **(c)** Vegetation probability image **(d)** Water probability image **(e)** Soil probability image
Note: Scene centre co-ordinates:11˚56'12.21" N 79˚49'50.26"E

The road segments are extracted by mapping the road pixels resulted from the super resolved map. However, it is seen that these roads are interrupted by the features such as avenue trees, buildings and soil. Such disconnected road segments are connected into meaningful road lines. The final road segments identified and unidentified, compared with the actual road network map are shown in Figure 5. The description about the classes identifiable from the three outputs at the sub-pixel scale is discussed in the Table 2.

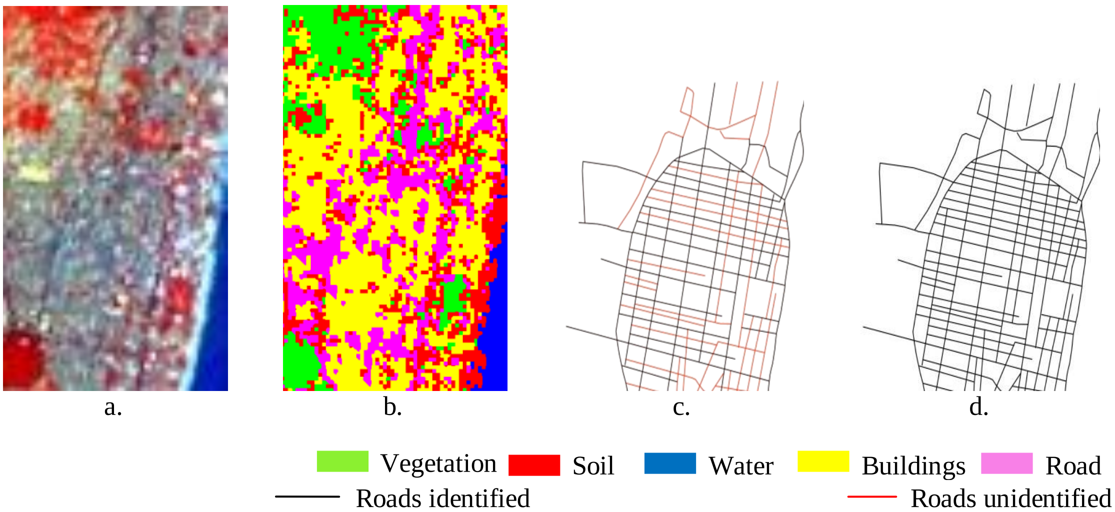


Figure 5. Super resolved output of Pondicherry image (a) Hyperion image (R (b55), G (b33), B (b15)) (b) SVM+SRM(HNN) (c) Road networks extracted from SVM+SRM(HNN) (d) Actual road network
Note: Scene centre co-ordinates:11˚56'12.21" N 79˚49'50.26"E

Table 2. Remarks on the classes identifiable from the results of super resolved map

Features	**SVM as an input for SRM (HNN)**
Broad Roads (15m)	Clearly identifiable in the super resolved map. In few parts of the output, shadow of the buildings is misclassified as road.
Narrow Roads (<9m)	Only few pixels represented the narrow roads but those pixels correctly represented the roads. Most of the narrow roads are classified as buildings and soil due to the presence of less fraction of road class being represented in the road probability image.
Avenue trees	Avenue trees are correctly classified as vegetation class ie, green cover.
Beach Sand	Beach sand is correctly identified as soil class in the super resolved output. The soil probability image is exactly represented which resulted in accurate super resolved map.
Parks	Classified as vegetation class ie green cover. Bharathi Park and Botanical garden are clearly identifiable from the super resolved map.
Buildings	Buildings are well classified.

6.2. Accuracy assessment and Validation

The accuracy assessment for the three outputs is provided in the Table 3. The overall accuracy of the SVM approaches is 92.97%.

For validating the results, the road segments were identified from the super resolution output. The correctness and completeness of the road networks extracted from the classification approach is estimated using the number of road segments identified and unidentified is shown in Table 4. The completeness and correctness are the common indices used to validate the road network analysis (Wiedemann and Ebner, 2000) as shown in (8) and (9) respectively. Thus, in this study, for the validation and quantitave analysis, we use

$$\text{Completeness} = L_a/L_r \tag{8}$$

where L_r is the total length of manually determined roads, L_a is the total length of automatically extracted roads.

$$\text{Correctness} = L_c/L_a \tag{9}$$

where L_a is the total length of automatically extracted roads and $L_a$is total length of the extracted roads that match the manually determined roads. From Table 4, it is seen that SRM with SVM as an input can achieve completeness of 0.594 and correctness of 0.863 from the 30m resolution Hyperion image.

Table 3. Classification accuracy of SRM for stratified random samples in 6 m resolution output

	SVM as an input for SRM(HNN)	
Classes	Producer's Accuracy	User's Accuracy
Soil	91.84%	91.84%
Vegetation	78.79%	92.86%
Water	92.00%	92.00%
Road	97.26%	91.03%
Buildings	96.05%	96.05%
Overall Accuracy	92.97%	
Kappa Statistics	0.9081	

Many authors (Sepheri, 2011; Rafiee, 2008; Song and Civco, 2004; Fauvel et al, 2008) have acclaimed the use of SVM for road network extraction. Few authors Benkouider et al (2011), Ghasemloo et al (2013), Mokhtarzade et al (2008) preferred to use Neural Network as an efficient technique to extract road networks. Though Sepheri (2011) used SVM in super resolution mapping, the novel combination of SVM as an input to the HNN based super resolution mapping is proved to be a potential technique to extract road networks.

Table 4. List of number of roads identified and unidentified for SVM as the input for super resolution mapping

Mapping approach	No. of road segments identified correctly	Actual no. of road segments	No. of road segments unidentified	Completeness= $\frac{L_a}{L_r}$	Correctness= $\frac{L_c}{L_a}$
SVM+SRM(HNN)	26	48	22	0.594	0.863

7. Conclusions

Since developing countries may not have access to high resolution images, they have to be contend with the moderate to coarse resolution images such as Landsat TM and Hyperion images. This work has demonstrated that it is possible to extract road network information from such images using super resolution mapping approach with SVM as an input mode (with 92.97% accuracy). Though it is known that the SVM works well in the road extraction process from satellite image, it is more efficient when combined with the super resolution mapping approach. Thus the HNN based super resolution mapping method proves to be a reliable approach for road network extraction when the soft classification input is from SVM.

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