Analysis of Various Road Pattern Recognition Methods for Satellite Images

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Abstract—Recently road extraction from satellite imagery has emerged as one of the hot topics in the research field. It is particularly employed in the city planning, cartography and to revise already detected roads in Geographic Information Systems (GIS) environment. Some of the several applications of road extraction are renewal of GIS database, reference for image registration, assistance for identification algorithms and fast mapping. Road extraction enables the road network to be truly presented in the object space when the image to ground systems transformation is carried out and it has been described as the method of detection and precise localization of roads in the image. Automatic road extraction attempts to simplify and speed up the road extraction process by focusing on automating all or few parts of this process.

In photogrammetry and digital image processing fields, road extraction is considered as a challenging issue. In this paper detailed survey has been carried out on various road extraction techniques from satellite images and their performances were analyzed.

Keywords— Particle filtering, kalman filtering, road extraction, Neural network and dense cloud points.

I. INTRODUCTION

Today satellite remote sensing systems provide large volumes of data that are invaluable in monitoring Earth resources and the effects of human activities. Road feature extraction from remotely sensed images has been a long term topic of research and because of its complexity is still a challenging topic. Urban road mapping from high spatial resolution images are an asset because they allow the discrimination of urban features, but they also bring new problems because, a lot of the urban features can be considered as noise. For example, cars, shadows, trees, etc hinder the discrimination of roads.

Level set method is a search algorithm that determines evolving curve’s boundary pixels the level set propagates as long as the speed function is greater than zero. For the road extraction problem speed function has to be greater than zero at the edges of the true road boundary. Therefore Level set is an efficient technique for extracting road.

[15] A Homogeneity characteristic of the pixel was used to extract the road feature from the satellite images. Gradient operation based road skeletal formation was applied to high resolution satellite images. This process of extraction was time consuming. Segmentation and image classification by neural network was used to extract the roads. Object oriented approach in GIS information. Light Shadow filled satellite images was extracted by skeletonization process. Urban roads were well extracted by dense point clouds divides the roads into patches curb detector was used to encode the road segments. The following chapter gives the detailed literature survey on the different methods for road map extraction.

II. METHODS FOR ROAD EXTRACTION

A. Road extraction using neural network

Road detection can be considered as the first step in road extraction, it is the process of assigning a value to each pixel that can be used as criteria of road and not-road pixels. The problem of road detection from high-resolution satellite images is performed using: 1) artificial neuronal network and 2) pixel spectral characteristics specially the red, green and near infra red channels. The motive is to find the homogeneity of roads in high resolution satellite images since homogeneity is a characteristic that can be recognized with respect to neighbor pixels, and their spectral information. The input requirements considered here are the spectral characteristics, road appearance and the road homogeneity.

The functioning of artificial neural networks are mainly based on simply processing units called neurons. The task associated with a neuron is to receive the activation values from its neighbors, compute an output based on its weighted input parameters and send that output to its neighbors. Road detection from satellite
images can be considered as a classification process in which pixels are divided into road and background classes. A back propagation neural network (BNN) with one hidden layer is used. Normalized spectral information in a window of (3 x3) around each pixel of RGB images are used, as 9 red neighbors pixels, 9 green neighbors pixels and 9 blue neighbors pixels to constitute the input vector of 27 neurons. The output layer consists of one neuron that represents the network output by a number between 0 and 1 as not road and road pixel, respectively.

The combination of both 27 input parameters made the network powerful in the detection of road and background, reducing also the request hidden layer and size iteration time. For accuracy assessment, we consider two parameters: the mean square error (MSE) and the Kappa coefficient. The MSE, proved to be the most reliable parameter to be used as termination condition. The Kappa coefficient, the overall accuracy parameter, is calculated by the same way as classification methods. The above discussed method is based on spectral characteristics of the pixel from satellite image. The neuronal net require a large coded data bases in their training stage that is drown using special software. Morphological operations are proposed to obtain the road cartography: grayscale erosion is applied to the extracted road by the proposed ANN system, followed by a binarization process. This process obtained very accurate results with less than 0.022 for the MSE.

### TABLE OF PERFORMANCE MEASURE

<table>
<thead>
<tr>
<th>Image</th>
<th>MSE</th>
<th>Accuracy Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. 1</td>
<td>0.0206</td>
<td>86.2%</td>
</tr>
<tr>
<td>No.2</td>
<td>0.0211</td>
<td>84.5%</td>
</tr>
</tbody>
</table>

### B. Road extraction based on level set, normalized cuts and mean shift methods:

The road extraction methodology discussed here is broadly divided into three steps: Preprocessing, road extraction and image overlaying. Under preprocessing a series of steps are taken to improve the image quality and to generate the elongated road network for further processing. Classification and filtering are performed under pre-processing. Level set method is a search algorithm that determines evolving curve’s boundary pixels the level set propagates as long as the speed function is greater than zero. For the road extraction problem speed function has to be greater than zero at the edges of the true road boundary. Therefore Level set is an efficient technique for extracting road. A level one classification was carried out by dividing the image into two classes: Roads and non-roads. Median filtering technique is applied to remove the clutter. The median is much less sensitive than the mean to extreme values called outliers. Median filtering is therefore better able to remove these outliers without reducing the sharpness of the image.

The three methods on road extraction are Level set method, normalized cuts and mean shift method. The level set method (LSM) tracks the evolution of a boundary front which is moving with a speed function that is normal to the boundary curve. In Normalized cut method for extracting road segments, each individual edge weight is a measure for the similarity between two connected pixels. The mean shift method is based on mean shift vector. It points toward the direction of maximum increase in the density. The Mean Shift procedure is obtained by successive computation of the Mean Shift vector and translation of the kernel by the Mean Shift vector. In image overlaying to illustrate the accuracy the extracted road region using is converted into binary image format.

The automatically extracted roads are compared with manually traced reference roads to perform accuracy assessment. Since roads have linear features, it is possible to use all the data rather than just sample points to conduct the accuracy assessment. Level set method has to be refined to extract the unidentified road regions. Of the three techniques tested mean shift is most robust all. The limitation of mean shift is fixed kernel bandwidth. Completeness of 93.81% and 86.45% were obtained using mean shift and normalized cut respectively compared to 77.35% using level set method which is still better than that obtained result. The correctness is 92.99% for level set and 93.1%, 98.25% for mean shift and Normalized cuts. The accuracy of mean shift is 87.72%, normalized cut is 85.14% compared to 73.09% in level set.

![CHART OF PERFORMANCE COMPARISON](image_url)
C. Road Extraction using Gradient Operation and Skeletal Ray Formation

The technique extracts the road mainly with the contribution of gradient operation and skeletal ray formation over the subjected satellite imagery. A coloring is performed followed by a morphological operation. Initially we convert the given satellite image SI which may be either a color image or a gray scale image into a binary image. The value of each pixel is restricted to either 0 or 1 in binary images. In a satellite image containing many small objects, the performance complexity of the image is increased due to the presence of such objects in the binary image. So we remove the small objects from it by morphologically opening the binary image. This morphological process removes all the connected components lesser than a particular area.

The filtering process is performed after the removal of small objects from the image. The filtering process is used for removing certain types of noise from the satellite image. The gradient method is used for performing smoothing processing an image and it reduces the noise in the image. In the smoothing process we perform the gradient operation two times. The threshold process is performed on each object array to reduce the values from the array. The dominant points and co-ordinate values are obtained by this process.

The dominant coordinate values are used to draw the tangent lines by connecting coordinate values with the neighboring pixel values. The illustrated tangent lines to all coordinates values are called skeletal rays. Next we mark midpoint values for two tangent lines. The midpoint values are detected for all object values and all the mid-point values are connected. After this process the boundary region areas in an image are identified. The boundary region values of all pixels are changed using 5 modulo operations and some coloring conditions are performed on the boundary pixel values. Basically four types of morphological operations are performed in binary image processing. They are erosion, dilation, opening and closing. Standard quality measures like completeness, correctness and quality are used for assessing the performance of the proposed system.

D. Road extraction based on LSE-LBF model

This proposed to use a level set evolution and local binary fitting based model for the extraction of roads and that is followed by morphological operations. Level set methods were used for capturing moving fronts and active contours model is used for segmenting objects in images using dynamic curves. Active contour models are of two types; parametric active contour models and geometric active contour. The parametric active contours are represented explicitly as parameterized curves in a Lagrangian framework, while the geometric active contours are represented implicitly as level sets of a two-dimensional function that evolves in an Eulerian framework.

The level-set method applies a function \( \Phi(p; t) \) to the space the interface inhabits, where \( p \) is a point in that space, \( t \) a point in time. The function is initialized at \( t = 0 \), and then a scheme is used to approximate the value of \( \Phi(p; t) \) over small time increments. First a mesh or a grid of points that covers the image is selected. A fine mesh gives more accurate the level-set method. Then the value of \( \Phi(p; t) \) is initialized at each point of the mesh. The function \( \Phi \) is defined as follows, for any point \( p \) in the mesh

\[
\Phi(p; t) = \pm d
\]

Where \( d \) is the distance from the point \( p \) to the curve at the time \( t = 0 \). The positive sign is used if the point \( p \) is outside the closed curve; the negative sign is used if the point \( p \) is inside the closed curve. A computationally intensive algorithm is used to set up the initial value of function \( \Phi \) at each of the mesh point. Morphological operations are a broad set of image processing operations that process images based on shapes. Morphological operations apply a structuring element to an input image, creating an output image of the same size. The value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors.

By choosing the size and shape of the neighborhood, one can construct a morphological operation that is sensitive to specific shapes in the input image. Two morphological operations have been used, namely, dilation and morphological closing. Using morphological operations after the LBF model aids the road network extraction. In this model the unwanted background regions are made to look black in color and the extracted network is white in color. In the performance analysis of this method of roadMap Extraction for the different values of C0 --closing function, Mask –w & Iterations values, were tested on different satellite images.

E. Road extraction using cloud basis neural network

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Gradient Method</th>
<th>ANN Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Completeness</td>
<td>72</td>
<td>69</td>
</tr>
<tr>
<td>Correctness</td>
<td>82</td>
<td>46</td>
</tr>
<tr>
<td>Accuracy</td>
<td>81</td>
<td>80</td>
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</table>
The processing comprises two fundamental and critical steps towards content analysis and image understanding i.e. image segmentation and classification. This proposes an approach for automatic road extraction from high resolution remotely sensed multi-spectral images, such as IKONOS or Quick Bird. While aerial imagery usually consists of three spectral bands, high resolution satellite data comprises four spectral bands with a better radiometric quality compared to film, but a worse geometric resolution. Therefore, strongly making use of the spectral properties of satellite imagery is a way to mitigate the geometric disadvantages and achieve results comparable to those from aerial imagery.

Classification of high-resolution satellite images using standard per-pixel approaches is difficult because of the high volume of data, as well as high spatial variability within the objects. One way to deal with this problem is to reduce the image complexity by dividing it into homogenous segments prior to classification. This has the added advantage that segments can not only be classified on basis of spectral information but on a host of other features such as neighborhood, size, texture and so forth. Segmentation of the images is carried out using the region based algorithms such as morphological marker based watershed transform by employing the advantages of multi-resolution framework and multi-scale gradient algorithms. The segmentation of the color images is obtained using watershed transform to get its homogenous regions. Classification technique is then applied into these homogenous regions taking the shape, texture and spectral properties of the regions.

Physical features in general have certain associations with spectral features, so they can be identified by using multi-spectral information from the remotely sensed images. However land use information cannot be determined by land cover information directly. Properties of objects can be further divided into three categories. They are Geometric, Spectral or thematic and Textural. Rather than treating image as set of pixels treat it as a set of objects therefore more information can be extracted, as with pixels only intensity values can be used. And with the construction of regions, knowledge is given to the system to classify. This is similar to the way human brain analyzes an image by breaking it down into various objects and uses features such as shape, texture, color and context along with the its cognizance powers to interpret the image. Therefore, dividing the image into regions and then opt for classification is better than per pixel classification. Hence cloud basis function neural network is used which is essentially a form of neural network with modification in radial basis function neural network.

Object based image analysis is heavily dependent on the quality and resolution of the image data. The object based approach enables the usage of various features, making full use of high resolution images information. Beyond purely spectral information, image objects contain a lot of additional attributes which can be used for classification and this method is more suitable and will be the trend for the high resolution remotely sensed data. Object-based approach has the advantage to produce compact objects which correspond to human eye perception of the environment and it reduces the variance problem of very high resolution satellite data. It also provides possibilities to bring in additional knowledge on the image objects of interest, on object inter-relations and relations to external map or GIS information.

### PERFORMANCE OF CLOUD BASIS NEURAL NETWORK FOR ROAD EXTRACTION FOR TWO CITIES

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Mumbai</th>
<th>Rome</th>
</tr>
</thead>
<tbody>
<tr>
<td>Completeness</td>
<td>94</td>
<td>90</td>
</tr>
<tr>
<td>Correctness</td>
<td>92</td>
<td>88</td>
</tr>
<tr>
<td>Accuracy</td>
<td>92</td>
<td>93</td>
</tr>
</tbody>
</table>

#### F. Road extraction using skeleton pruning by discrete curve evolution

The aim of the skeletonization is to extract a region-based shape feature representing the general form of an object. There are three major skeletonization techniques: detecting ridges in distance map of the boundary points calculating the Voronoi diagram generated by the boundary points and the layer by layer erosion called thinning. All these algorithms need skeleton pruning and there are mainly two types of pruning methods: based on significance measures assigned to skeleton points and boundary smoothing before extracting the skeletons. But these skeleton pruning algorithms have many drawbacks. First, many of them not guaranteed to preserve the topology and second drawback is that main skeleton branches are shorten to some extent and short skeleton branches are not removed completely, which complicates the structure of skeletons.

In particular the skeleton generating approaches suffer from the fact that a small protrusion on the boundary may result in a large skeleton branch, which is an intrinsic problem of the definition of the skeleton, since the mapping of boundary points to the skeleton points is not continuous. So use skeleton pruning by discrete curve evolution. The method completely removes protrusions without displacing the boundary points, and consequently, without displacing the remaining skeleton points. Spurious or redundant branches are completely removed while the main branches are not shorten. The
important observation of this method is that it is possible to perform a topology preserving skeleton pruning based on a contour partition into curve segments. The statistical region merging is used in the image segmentation step followed by thresholding. In the next step skeleton pruning by discrete curve evolution is used to extract road network. The method is tested on different high resolution test images.

G. Road extraction using dense cloud points

This describes a method for extracting roads from a large scale unstructured 3D point cloud of an urban environment consisting of many superimposed scans taken at different times. Given a road map and a point cloud, the system automatically separates road surfaces from the rest of the point cloud. Starting with an approximate map of the road network given in the form of 2D intersection locations connected by polylines, first produce a 3D representation of the map by optimizing Cardinal splines to minimize the distances to points of the cloud under continuity constraints. And then divide the road network into independent patches, making it feasible to process a large point cloud with a small in-memory working set.

For each patch, fit a 2D active contour to an attractor function with peaks at small vertical discontinuities to predict the locations of curbs. Finally, the output a set of labeled points, where points lying within the active contour are tagged as “road” and the others are not. The method takes input a point cloud and an approximate 2D map of a road network and it produces a model of the road boundaries along with a tag for every point in the cloud indicating whether it is part of a road or not. It is intended to work for road networks that can be represented as a connected set of smooth continuous surfaces of slowly changing width and elevation delimited partially by elevation discontinuities, as are commonly found in urban environments. The 2D map of the road network onto the given 3D point cloud in a manner that preserves the road network’s topology and ensures geometric continuity – creating a map spline. Then split the map spline into independent parts, road patches, and extract a sub cloud of relevant points for each road patch. These sub clouds are small enough and can be processed independently with an out-of-core framework that requires small working sets.

For each sub cloud, build a 2D attractor map that estimates the locations of elevation discontinuities. Then, compute a ribbon snake for each road patch by optimizing an active contour that aims to maintain smoothness of its boundary while fitting its boundary to likely predictions in the attractor map. Finally, the points in the respective sub cloud that fall inside the active contour are labeled as road points. In the performance analysis of this method of road map extraction correctness, completeness and accuracy of curb detector Attractor functions was compared.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Attractor fn An</th>
<th>Attractor fn An step</th>
<th>Attractor fn An exp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correctness</td>
<td>88.7</td>
<td>83.2</td>
<td>86.3</td>
</tr>
<tr>
<td>Completeness</td>
<td>86.2</td>
<td>95.7</td>
<td>94</td>
</tr>
<tr>
<td>Quality</td>
<td>77.7</td>
<td>80.2</td>
<td>81.8</td>
</tr>
</tbody>
</table>

H. Grid density based approach for finding clusters in satellite images

High resolution and high dimensional satellite images cause problems for clustering methods due to clusters of different sizes, shapes and densities as they contain huge amount of data. Due to this reason, most algorithms for clustering satellite data sacrifice the correctness of their results for fast processing time. The processing time may be greatly influenced by the use of grids. Discussed a grid density based clustering method for detecting the clusters present in satellite images. The clustering is based on both the band values as well as the texture features in the satellite images.

The idea behind density based clustering approach is that the density of points within a cluster is higher as compared to those outside of it DBSCAN is a density-based clustering algorithm capable of discovering clusters of various shapes even in presence of noise. The key idea of DBSCAN is that for each point of a cluster, the neighborhood of a given radius has to contain at least a minimum number of points (MinPts) and the density in the neighborhood has to exceed some threshold. It is difficult to estimate suitable values for the two parameters (MinPts) for different datasets. Another drawback of this technique is the high computational complexity because of neighborhood query for each object. This step is very expensive especially when the algorithm runs on very large datasets. Therefore, spatial index structures are used for large datasets. Another drawback of DBSCAN is that due to the use of the global density parameters, it fails to detect embedded or nested clusters.

Grid based methods divide the data space into a finite number of cells that form a grid structure on which the clustering operations are performed. This is high probability that all data points that fall into the same grid cell belong to the same cluster. Therefore all data points belonging to the same cell can be aggregated and treated as one object. It is due to this nature that grid-based clustering algorithms are computationally efficient

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which depends on the number of cells in each dimension in the quantized space. It has many advantages such as the total number of the grid cells is independent of the number of data points and is insensitive to the order of input data points. Some popular grid based clustering techniques uses a multi-resolution approach to perform cluster analysis. The advantage of that it is query-independent and easy to parallelize. However the shapes of clusters have horizontal or vertical boundaries but no diagonal boundary is detected. This method is used for grid based clustering in satellite images and texture feature extraction. The homogeneity factor, CPU processing time and DB index of the hard and soft smoothing texture extraction was compared.

### PERFORMANCE MEASURE

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Homogeneity factor</th>
<th>Processing Time</th>
<th>DB index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hard cluster</td>
<td>17.82</td>
<td>0.78s</td>
<td>23.79</td>
</tr>
<tr>
<td>Completeness</td>
<td>12.63</td>
<td>0.79s</td>
<td>16.60</td>
</tr>
</tbody>
</table>

**I. Road extraction using particle filtering and extended Kalman filtering**

First, Extended Kalman Filtering traces a road until a stopping criterion is met. Then, instead of terminating the process, the results are passed to the PF algorithm which tries to find the continuation of the road after a possible obstacle or to identify all possible road branches that might exist on the other side of a road junction.

Fig 1 (a) First road segment extracted by the EKF module. (b) Particles of the PF module

Fig 1 a shows the extraction of the first road segment by the EKF module. The EKF module has traced the road until it encounters the junction. At this point, the EKF module hands over the process to the PF module, which distributes the particles in the way shown in fig.b.

For further improvement, modify the procedure for obtaining the measurements by decoupling this process from the current state prediction of the filter. Removing the dependence of the measurement data to the predicted state reduces the potential for instability of the road-tracing algorithm. The proposed algorithm has been tested on an IRS satellite image with 5.8 m spatial resolution and IKONOS of 0.8 m resolution. All roads in the satellite images were extracted clearly and this robust.

**III. RESULTS AND DISCUSSION**

Analysis of the various survey results dealt with the completeness, correctness and accuracy measure in the road map extraction for different satellite images and complexity conditions. It is proposed to obtain a better completeness, correctness and accuracy in the road map extraction in complex urban areas where the road network will be very congested. From the survey is clear that the road extraction using particle filtering and extended Kalman filtering shows better results.

**IV. CONCLUSION**

This article describes a survey of different method for extracting the road network from high resolution satellite images. A topologically correct graph of the road network is extracted. Then the different methods performance analysis was carried out. Correctness, Completeness and quality of extraction were estimated for the different techniques. From the literature analysis it is inferred that road extraction by the method of filtering and segmentation produces 0.98 completeness and correctness in road extraction in complex urban areas.

**REFERENCES**


