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A Novel Approach for Detection of Road Junctions in Satellite Images Using an Improved Ridge Detector

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Abstract: The road network is an important component of the infrastructure in the country. Now-a-days, the road network varies at fast rate since of city enlargement. Therefore up-to-date and exact information on the road networks is of fundamental importance. Road detection is a complex task because of tall buildings, large vehicles and trees. Most of the existing system only detect and extract the road from satellite image. It does not detect the road junctions. To solve this problem, use an improved ridge detector in proposed mechanism. Here the ridge detector is used for detect the ridges from the road image and non road regions are removed from the road region by using Probabilistic Support Vector Machines (P-SVM) classifier. We use a modified CSNN, termed CSNN Complementary Information Integration (CSNN-CII), for integrating the complimentary information from the outputs of ridges and region-based processing. The detected network is improved by using region growing technique. Finally MAT-based road hypothesis verification is used for filtering unwanted layers. In this paper, we presented a junction detector based on an improved ridge detector using region growing which is used for extract the junctions and improve the vicinity of junctions.

Key words: Region growing · Improved ridge detector · Junction detection

INTRODUCTION

Automated road network extraction from remotely sensed imagery is a difficult and significant research theme [1]. Roads are the backbone and essential modes of transportation, providing many different supports for human civilization [2].

Types of Roads:

- Local roads
- Collector and distributor roads
- Sub-arterial and arterial roads

These are the major highways, motorways and freeways Also, while not technically a road, bikeways provide the general community with an alternative means of travel.

Local Roads: Local roads are largely the neighbourhood street system. These roads are relatively free of through traffic and mostly handle local traffic. The challenge in these areas is to offer a high level of safety and adequate access to neighbourhood services. Local roads are normally maintained by the local authority.

Collector and Distributor Roads: Collector and distributor roads are the roads which are connect the communities to the main sub-arterial and arterial roads in Queensland. In general, they permit for the transport of agricultural goods and the like, to main highways for transport to markets. Similarly, in an urban environment they tend to be the roads connecting suburbs to the main freeways.

Sub-Arterial and Arterial Roads: The Sub-arterial and arterial roads are the main connecting roads across

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Queensland. They have highways, freeways and motorways. On the common day, they handle huge volumes of freight and passenger vehicles.

Properties of Road Surfaces

Longitudinal Characteristics: Longitudinal characteristics are calculated a long wheel path of the road surface. Here the surface features are Micro texture, macro texture, Mega texture and Roughness.

Transverse Characteristics: It has generally been calculated on a sampling basis using 1.2 m straight edges [3]. Multi laser measuring methods are increasingly being used to compute rutting for network level condition surveys.

Skid Resistance: Routine skid resistance measurements are typically taken at relatively low speed skid resistance, such skid resistance measurements can be regarded as an indirect measure of micro texture.

Classification of Road Junction: The different categories of junctions are designed for the purpose of traffic safety. This different kind of junctions has different properties and construction models. We categorized the junctions into four main classifications. [4] There are [5] Simple, Complex, Roundabout and Motorway.

Simple junctions: It has three or more road arms without islands in the center.

Complex junction: complex junctions have islands in the center

Roundabout: Roundabout junction is a simple and complex junction that is defined in two dimensional spaces.

Motorway junction: It is defined in three dimensional spaces.

Related Works: R. Gecena *et al*. proposed an automatic road extraction method which is applied to four dissimilar satellite images (SPOT, IKONOS, QUICKBIRD, ASTER) with various resolutions that belong to Ankara city of Turkey. The system finds out the effect of the resolution on the automatically extracted roads. usually, automated road extraction method consider four steps; there are roads sharpening, roads finding, roads drawing and relating to extracted roads to each other. These processes are applied for four satellite images individually. Finally, the accuracy of produced results was tested with the GIS data layer that represents the reality [6]. However it only detects the roads from the satellite image. It does not detect the road junctions.

Xiangyun Hu *et al*. proposed an integrated processing of high resolution imagery and LIDAR (Light Detection and Ranging) data for automatic extraction of grid structured urban road network. This method first detects the primitives or clues of the roads and the contextual targets from the colour image and lidar data by segmentation. Evidences of road existing are contained in the primitives. The candidate road stripes are discovered by an iterative Hough transform algorithm technique. At last the road network is formed by topology analysis [7]. However adaptive threshold determination in the multi-step processing is does not consider for performance improvement.

Uwe Bacher *et al*. proposed an automatic extraction of road from high resolution multispectral imagery, such as IKONOS or Quick bird, in rural areas. The extraction process initialise with the extraction of Steger lines in all spectral channels. The lines are represented as cues for roads to create training areas for automatic supervised classification process. The final result of the classification, the road class image with well known features, is used as an extra source for the extraction of road candidates. A new verification procedure for road hypotheses creates use of geometric conditions of roads by calculating the road energy from the road class image. From the verified road hypotheses a final road network is created by first bridging small gaps based on a weighted graph and then searching for missing connections in the network by calculating local detour factors [8]. However it does not use the spectral properties of roads together with the road width, to automatically classify the roads into different road classes.

Sukhendu Das *et al*. proposed an automatic road extraction technique. Roads are expected to be locally linear. Hence, we extract the local orientation from the image of the road network in the DSM. Our method of obtaining the dominant direction using Singular Value Decomposition (SVD) of the gradient (obtained using multiscale) matrix, for orientation estimation to extract road segments, is efficient and produces more robust results. Also they used CSNN (Complementary Information Integration)-based Integrator to segment the class from P-SVM and linear edge map obtained from DSM. Post processing is a refinement process which is necessary to discard the false segments and it does not belong to roads. Segment linking is used to separate nearby segments by a small distance and then regenerate the road segment properly. RPS approach is necessary to discard few large patches of non road structures which appear to be fused to roads. MAT-Based Hypothesis Verification is used to eliminate the patches appearing due to parking areas and rooftops which are attached with road segments [9]. However it only detect the road it does not used for automatically detect the junction.

Proposed Methodology: Roads are the backbone and essential modes of transportation, it providing many different supports for human civilization. The process of road extraction and junction detection from high-resolution satellite images is a complex task. Most of the existing system was able to effectively extract major sections of the road network from high-resolution multispectral satellite images. A major problem however is that the road network as is detected, fails in the vicinity of junctions since the ridge model does not hold anymore. To solve this problem, use an improved ridge detector in proposed mechanism.

Road Feature Extraction: The road images are seen as narrow ridges or valleys in the intensity surface. Ridge has been occurs when intensity values of connected sequence of pixels in the sequence has higher or lower values than the neighbouring sequence. The different images have various profiles of the ridges which are differ from their shape and intensity values. Here extract all ridges in the input image by using ridge detection scheme. Ridge detection is carry out based on polynomial interpolation to compute pixels belonging to road construction in the given input image. By using a Hessian matrix of the Taylor polynomial the line direction can be computed. Each and every pixel in the image has a gradient and curvature information. This information is used to categorize a pixel in a lot of topological classes based on their sign. This model find out a least squares fit of a polynomial F to the input image data over a window of size $N = w^2$ with window size w.

The origin is elected in the central pixel of the window. The polynomial value F in pixel (i, j) is specified by;

$$F(i, j, \vec{\theta}) = a_1 + a_2 i + a_3 j + a_4 i^2 + a_5 ij + a_6 j^2 \quad (1)$$

$$= \vec{m}^T \vec{\theta} \quad (2)$$

$$\vec{m} = [\ 1\ i\ j\ i^2\ ij_2]^T \quad (3)$$

$$\vec{\theta} = [a_1 \ldots \ldots \ldots \ldots \ldots .. a_6]^T \quad (4)$$

where,

$\vec{\theta}$ - Least-squares solution

$\vec{x}$ - Image data containing the intensity value I(i, j) in each pixel (i, j).

Based on the parameters $\vec{\theta}$ of the interpolated surface F, the gradient and Hessian in an individual pixels can be computed.

$$\text{Gradient (I)} = \begin{bmatrix} \frac{\partial I}{\partial x} \frac{\partial I}{\partial y} \end{bmatrix} \quad (5)$$

$$\text{Hessian (I)} = \begin{bmatrix} \frac{\partial^2 I}{\partial x^2} & \frac{\partial^2 I}{\partial x \partial y} \\ \frac{\partial^2 I}{\partial y \partial x} & \frac{\partial^2 I}{\partial y^2} \end{bmatrix} \quad (6)$$

Based on the gradient and eigenvalues of the Hessian, each pixel in the image can be allocating a topological class based on the sign of the gradient and eigenvalues. For example Classification of image structure.

‖G‖	λ_1	λ_2	Class
0	0	0	Flat
0	-	-	Peak
0	+	+	valley
0	-	0	ridge
0	+	0	valley
+	0	0	slope
+	_	-	slope
+	+	+	slope

For each point of the image the two principle curvatures λ_1 and λ_2 of the intensity surface can be computed and arranged. Here – symbol represented the values significantly smaller than zero. + Symbol represents values significantly larger than zero. Here the ridges are extracted from the image.

Region-Based Techniques: The interaction of the user is essential to create the set of training samples for SVM. The positive and negative samples denoted the road and non road category form the training set. Here probabilities for each pixel belonging to the road or non road regions are computed by the Probabilistic SVM (P-SVM). The non road regions are removed from the road region by using Probabilistic Support Vector Machines (P-SVM) classifier.

CSNN-CII to Integrate Road Regions and Ridges: Constraint satisfaction neural network (CSNN) is used for segmentation which is done by initialise the neurons. In that each and every layer contains many neurons. Here each neuron contains two fields: probability and rank. The rank field stores the probability rank in a decreasing order for that neuron. The initial class probability is done from the output of P-SVM. The P-SVM produced a soft class labels which are used to compute ranks. The huge probability value given to the neurons of the winner class and lower probability values are given to other classes. Neurons with same coordinates in each layer hold the probability that the pixel belongs to the segments. We use a modified CSNN, termed CSNN Complementary Information Integration (CSNN-CII), for integrating the complimentary information from the outputs of ridges and region-based processing.

Region Growing Technique: The detection is based on an initially detected road network using a ridge detector. Here verify the content and quality of the derived information and demonstrate which information is benefit for detect the junctions. Region growing scheme is used for improve the detected network. Basically the road network is broken at junctions. The flat spot area is seen clearly at the center of the junction. However the flat spot also occurred by buildings, wall and another structures. To solve this region growing scheme is performed which continuously grows region starting initial region to form homogeneous area in the image. In this case pixel will be added in the region if it is adjacent to another pixel in the region that has an intensity value that less than the given threshold T. The threshold value will be adjusted dynamically based on the mean and standard deviation of the region as it is being grown.

The adaptation equation is based on an algorithm by;

$$T^{t+1} = (1 - \min(0.8, \frac{\sigma_{region}}{\mu_{region}})).T^t$$

Here $T^0 = T$. This adaptive threshold value does not larger than the initial threshold T value. It becomes a much smaller value.

MAT-Based Hypothesis Verification: A MAT-based road hypothesis is created by using the knowledge about the properties of road segments. This requires a priori knowledge of contextual information that means relations between roads and other objects like trees, parking lots and buildings to be integrated into the road extraction and junction detection approaches.

Medial-Axis-Transform-based hypothesis verification is used for remove the connected non road structures from the output. MAT-based road hypothesis verification for filtering road layers. Thus, the accuracy of extracting junction and improve their vicinity from satellite images has improved to a great extent, producing the desired road layer.

Algorithm:
Input: Satellite Roadmap
Output: Junction detection with improved vicinity
Stage 1:
Step 1: Select the Satellite Roadmap image
Step 2: Compute gradient and Hessian of individual pixels
Step 3: Extract road ridges by using ridge detector
Step 4: Separate road regions from non road region by using P-SVM
Step 5: Integrate ridges and region-based processing outputs using CSNN-CII
Stage 2:
Step 6: Eliminate undesired patches and unnecessary artifacts from CSNN-CII output by using Post process
Step 7: Improve the detected network by using region growing technique
Step 8: MAT-based road hypothesis verification for filtering road layer

Experimental Results: The existing system of Multistage Framework to Extract Road is compared with proposed Road junction detection using an improved ridge detector method. Final results proved that the proposed methodology works produces better results than the existing methodology. This performance evaluation is done based on the performance metrics called the precision, recall and accuracy. This performance analysis is represented in the graphical format which is explained in the detailed manner in the proceeding sections.

Precision: Precision is defined as the Percentage of correct predicted results from given input. The precision value should be more in the proposed methodology than the existing approach for the better system performance.

Precision is calculated by using following equation.

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

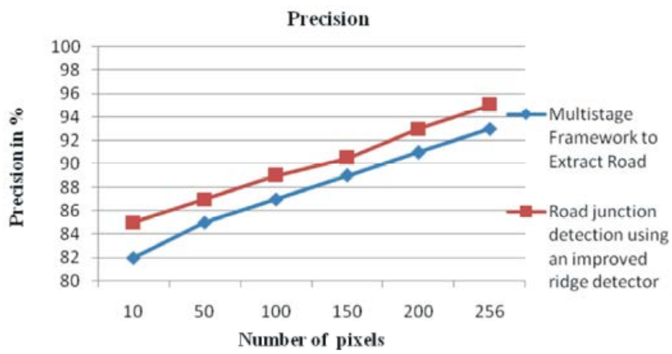

Fig. 1: Precision Comparison

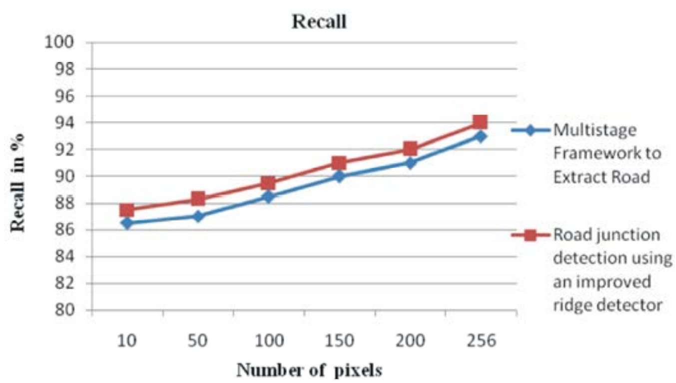

Fig. 2: Recall Comparison

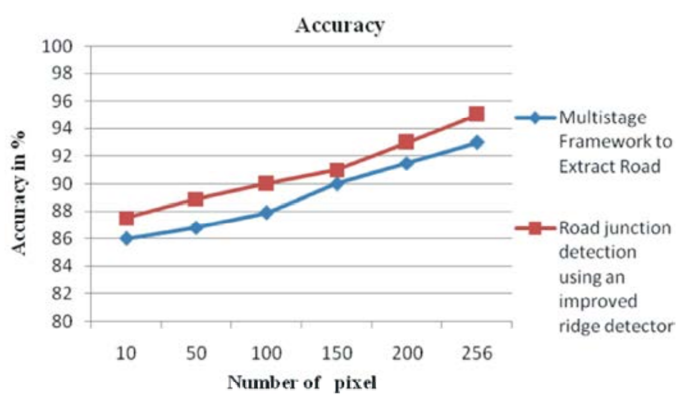

Fig. 3: Accuracy Comparison

The graphical representation is given in the following Figure 1.

In this figure x axis plots the number of pixels and y axis plots the precision value. From the above graph it can be proved that the proposed methodology provides better result than the existing approach.

Recall: The recall or true positive rate (TP) is the proportion of positive cases that were correctly identified, as calculated using the equation:

$$\text{Recall} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{True Negative}}$$

The graphical representation of recall value is plotted in the following Figure 2.

In this figure x axis plots the number of pixels and y axis plots the recall value. From the above graph it can be proved that the proposed methodology provides better result than the existing.

Accuracy: Accuracy is defined as the degree of generating the experimental output that is matches with the expected output. The accuracy is calculated by using the following equation

$$Accuracy = \frac{True\ Pisitive + False\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}$$

The degree of correct identification of junctions among the road images should be more in the proposed approach which is evaluated in the following graphical representation.

In this figure x axis plots the number of pixels and y axis plots the accuracy value. From the above graph it can be proved that the proposed methodology provides better result than the existing approach.

CONCLUSION

We presented a junction detector based on an improved ridge detector using region growing technique. The detector is specifically tuned towards detection of road junctions in huge resolution images, where we observe a clear deviation of the simple line model especially in the vicinity of junctions. Region growing is a simple model which is used to extend the performance of the basic ridge detector. The proposed system is used to extract the junction and improve the vicinity of junctions. The experimental tests have been conducted to prove that the proposed approach can provide better result than the existing approach in terms of improved accuracy, precision and recall.

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