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# An Automatic Approach for the Extraction of Road Junctions from High-Resolution Aerial Images

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## Abstract

The problem of locating road junctions has received much less attention than the extraction of roads networks from high resolution aerial images. The problem of road detection has been in the minds of researchers for the last 30 years where junction detection is a relatively newer problem and some interesting work in this direction has been done in the last decade. The exact localization of junctions has paramount importance in the field autonomous driving vehicles. Thus, in this paper, we present a naive but a very effective road junction detector. The detector has been tested on a number of rural images and its accuracy is very high.

**Keywords**: road junctions, high-resolution aerial images, rural areas.

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## I. Introduction

Road crossings or junctions are places of the road topology at which two or more different road segments are connected with each other. Systems which are built for the automatic detection of roads often neglect the extraction of road crossings. The problem for the location of road crossings lies in their great variability. Road crossings do not have sufficient local information so that they can be readily extracted from the road network as compared with the extraction of roads where disturbances like shadows can be detected and bridged based on the knowledge that roads are linear locally.

A junction detector should satisfy a number of important criteria: all the true junctions should be detected, no false junctions should be detected, junction points should be well localised, the junction detector should be robust with respect to noise and the junction detector should be efficient in terms of time and memory resources. This paper proceeds as follows. The related works are presented in the next section. Section III gives details of the system's design and implementation. The system has been tested and evaluated in section IV. Finally, section V concludes the paper with a brief outlook n future research.

## II. Related Works

One of the earliest works on road junctions in the context of autonomous driving vehicles was done in 1986. However, images were obtained from a camera fixed to a ground-based vehicle which was able to travel at a maximum speed of 8 km/hr [1]. The system known as ALVINN VC [2] was able to detect simple road intersections by a camera fixed to the vehicle which had a viewing distance of 9m. However, taking ground images has a serious drawback as the world is not flat and this causes significant difficult when junctions are located on inclined ground. The researchers used an artificial neural network to locate road junctions. In [3], the researchers modeled the road network using graph theory where the roads represented edges and the junctions represented vertices. A multi-resolution approach was used to locate the junctions. The work proposed used images obtained from rural areas where there were no other linear structures like building.

Many junction detection algorithms relied on the fact that road junctions are basically corners and that they could be extracted using corner detecting strategies. The most popular among these was a template-based corner detector. In this strategy, we must first develop a set of corner templates oriented in different directions and then determine the similarity between these templates and all the sub windows of the grey level image [4][5][6]. The templates also contain information about the grey level intensity and the direction of image pixels. A high similarity between the template and the image indicates a corner.

A geometry-based technique also operates directly on grayscale images. Here we make the assumption that corner points are points where the edge strength is high and the rate of change of gradient direction is maximum at a corner point. All points that are above a threshold are extracted as corner points [7]. There are many problems with this approach: firstly, the threshold value used for each image is quite different; secondly, the corners are not well localised; thirdly, they perform poorly in the presence of noise and a further problem is that too many corners are extracted in practice. A third technique consists of first extracting all the edges in an image. The edges are then chain-coded based on their strength and direction. Then the algorithm searches for significant turnings at the boundary [8]. This kind of corner detector also suffers from the high algorithm complexity, as multiple steps are needed. Also, errors in the edge extraction step will lead to poor results.

Barsi et al. [9] used a feed-forward neural network to locate junctions with three or four arms. They used only black and white images. The recognition accuracy was above 90% and was found to be better than traditional methods. A similar approach was repeated in [10] in order to reduce the false alarm rate. In [11], the road junctions were represented by geometric transformations using the Hough- and radon- transformations. Different types of junctions were analysed in different angles in order to find similarities between them. Although, this method is able to extract many junctions, they are not well localised. Furthermore, the results have not been evaluated properly as only a few small and simple images were used in the testing phase.

Negri at al. [12] proposed a novel approach where information about junctions can be used to improve the road extraction process in an urban setting with high-resolution images. Experimental results show that the completeness and correctness factor is above 90% for many of the images used in the test set. In [13], the authors proposed a new approach using a Ziplock snake. The method was tested with high-resolution images with a ground resolution of 0.1m from suburban and urban areas. This approach is able to handle problems caused by road markings and shadows from natural or man-made objects. Prior knowledge from an existing geospatial database was found to improve the junction extraction process by a significant amount. The authors mentioned that the wise selection of feature parameters and the use of balloon snakes can considerably improve the results.

Hu at al. [14] presents a sophisticated approach for the extraction of the road network from high-resolution images obtained from urban and sub-urban regions. Their work is based on the tracking of road footprints. Seeding can be done manually or automatically. Experimental evaluation shows that all the three widely used measures (completeness, correctness and quality) are above 80%. This paper also provides a very good survey of existing techniques.

Although not specifically a junction-detection work, this algorithm also detects the junctions with very high localisation accuracy. In [15], a knowledge-based approach for the extraction of road-junctions from high-resolution aerial images was presented. The system was tested with black and white images having a resolution of 0.4m taken from open rural areas.

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Prior knowledge from a geospatial database was also used as in [13] but the results have not been evaluated quantitatively.

Ravanbakhsh et al. [16] presented a novel piece of work for the extraction of so-called road junction islands from high-resolution aerial images using level sets. They evaluated their approach using 9 images which contained 17 such islands. The mean completeness factor was found to be 71%, the completeness factor was at 87% and the geometrical accuracy was estimated at 0.22m. Another novel work which performs the automatic extraction of road junctions from raster maps is presented in [17]. Their procedure is able to localise junctions with very high geometrical accuracy and is also able to determine the type of intersection as well.

An innovative technique to detect road intersections is described in [18]. They relied on GPS data received from regular moving vehicles rather than computer vision techniques to trace the road network and thereafter to extract the road junctions. Using the same procedure, the road network as well could be enhanced. A recent work in junction extraction [19] use the information received from ridges and valleys to localise junctions. Their approach was evaluate on both synthetic and real-life images and was found to be highly robust to noise.

## III. Methodology

In this project, we are proposing a template-based approach which will be applied after all the lines have been extracted and small gaps bridged. In this approach, corners are defined as intersection points or junction points between two or more straight-line segments. This template-based approach is thus suitable for the extraction of L, X, Y, T and → junctions. The following crossings are not modelled: roundabouts and complex crossings with overpasses. These are very important but they form only a negligible percentage of the road network and thus are not usually considered.

Our algorithm is able to extract most junctions in an image and the biggest advantage is that the corners are well localised. However, it has several drawbacks because it relies entirely on the line extraction step. Junctions for which the line extraction step is not very good will not be extracted and the numbers of corner extracted are too many when many noisy lines are present. The junction detector algorithm is based on the two templates shown below. We have used different colours so that we can better explain how the templates work.

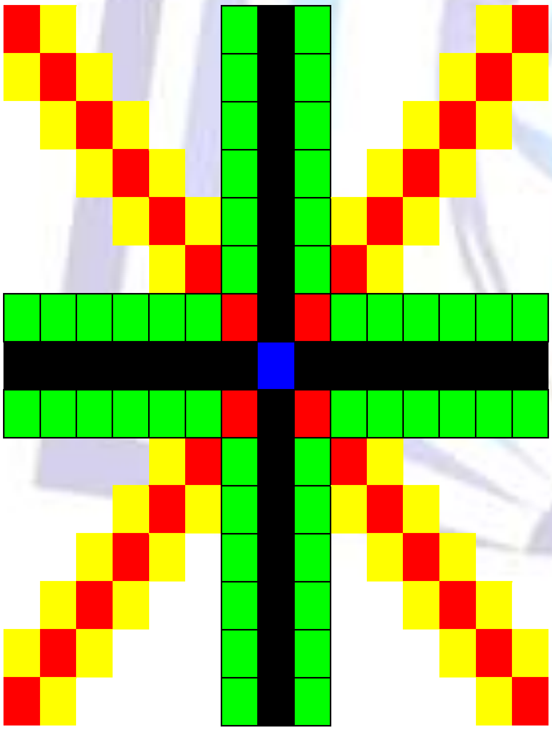

**Figure 1. Showing Rotating Arms**

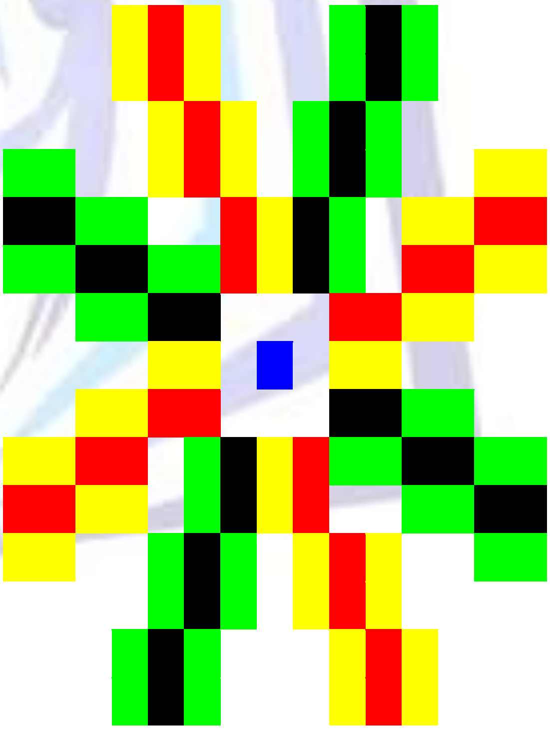

**Figure 2. Showing Rotating Arms**

Those squares that are painted black and red are the actual arms of the template. From Figure 1, we can see that the arms can rotate in the following direction: 0, 45, 90, 135, 180, 225, 270 and 315. From Figure 2, we can see that the arms can also detect junctions along the following directions: 22.5, 67.5, 112.5, 157.5, 202.5, 247.5, 292.5 and 337.5. Thus, we have a total of 15 arms which is used to locate junctions from all directions. This is necessary as we do not always have ideal T, X and Y junctions. The road segments can be located at any angle to the others. The positions of each cell are pre-defined to avoid floating-time computations at processing time.

The templates are convolved with the binary image after the line extraction and bridging steps are completed. For the centre pixel (blue pixel) to be localised as being located on a road crossing, a template must satisfy the following conditions: all the pixels on at least three non-adjacent arms must lie on lines in the binary image and if the first condition is satisfied then we need to calculate the number of white pixels surrounding the three non-adjacent arms. This is done by counting the number of white pixels corresponding to the locations shown by the yellow and green squares. If the number of white pixels is above a certain experimentally determined threshold, then the blue square is considered to be located on the centre-point of a road junction.

## IV. Evaluation

Four different measures are used to evaluate the junction detector: completeness, correctness, redundancy rate, stability and good localisation. The junction detection algorithm was tested on 33 grayscale images. Each image had a resolution of 320 x 320 pixels. The different measures are explained below.

**Completeness** = (total no. of true junctions extracted/total no. of junctions in image) x 100 %.

**Correctness** = (total no. of true junctions extracted/total no. of junctions extracted) x 100 %.

**Redundancy** = (total no. of non-junction extracted/total no. of junctions extracted) x 100 %.

**Stability** = (total no. of junctions - total no. of non-junction)/total no. of junctions x 100%.

From the 33 images we selected, a total number of 233 junctions were extracted. Our template-based junction detector could only localised 191 of them. Due to the presence of noisy lines, 62 non-junctions were also extracted. The following results were obtained: completeness: 85%, correctness: 75%, redundancy: 30% and stability: 73%.

Our junction localiser works well with respect to completeness but performs less better with regards to correctness, redundancy and stability. However, the performance results are still satisfactory as the values are still quite high. Much of this degradation in performance is because of the extraction of non-road junctions which affects the correctness, redundancy and stability measures. These could be increased by then removal of noisy lines by the application of larger filters during the line extraction process. Using longer arms will also reduce the occurrence of wrongly extracted junctions but the process will then take more time.

The completeness factor is completely dependent upon the line extraction process. Therefore, junctions that could not be extracted by the road extraction algorithm would definitely be undetectable by the junction localiser. One way to enhance this process is to develop a template-based algorithm that would be run on the original grayscale image directly instead of converting to a binary image first. The template would consider attributes like edge strength, direction and spectral value of neighbouring pixels to evaluate the possibility for a junction. Those regions that satisfy all the imposed conditions would be localised as junctions. However, this algorithm would be many times more computationally expensive as it would have to deal with several parameters instead of very simple binary images.

One more measure that could have been used here was localization accuracy but this is quite difficult to quantify as we need to select the centre-point of each junction manually and then compare with those that are extracted. One way to do that is to measure the Euclidean distance in pixel between the actual junction and the one that is localised by the algorithm. Although the measure was not computed and quantified, we can see from the test results that the algorithm performs very well in this respect. It is able to localised most true junctions with very high accuracy. This can be seen in the following figures below. The extracted junctions are shown using small red rectangles.

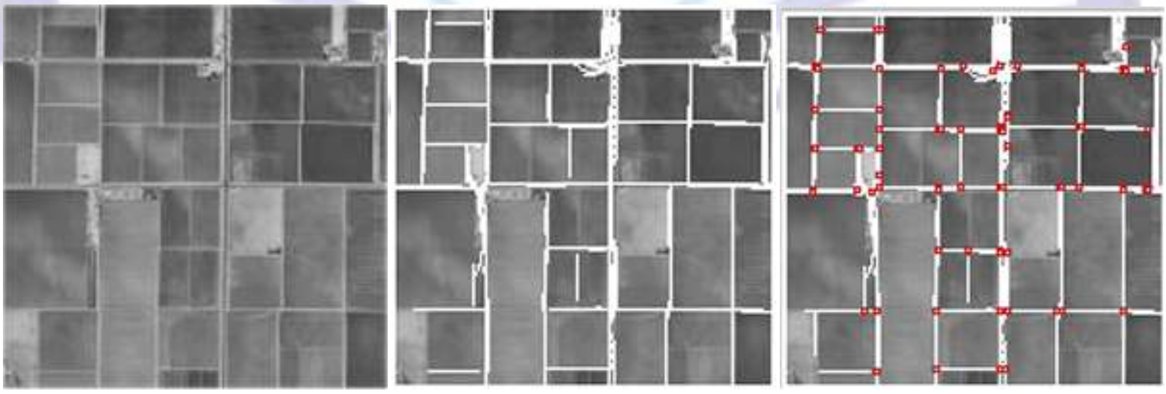

Figure 3a. Test Image 1　　Figure 3b. Line Extraction　　Figure 3c. Extracted Junctions

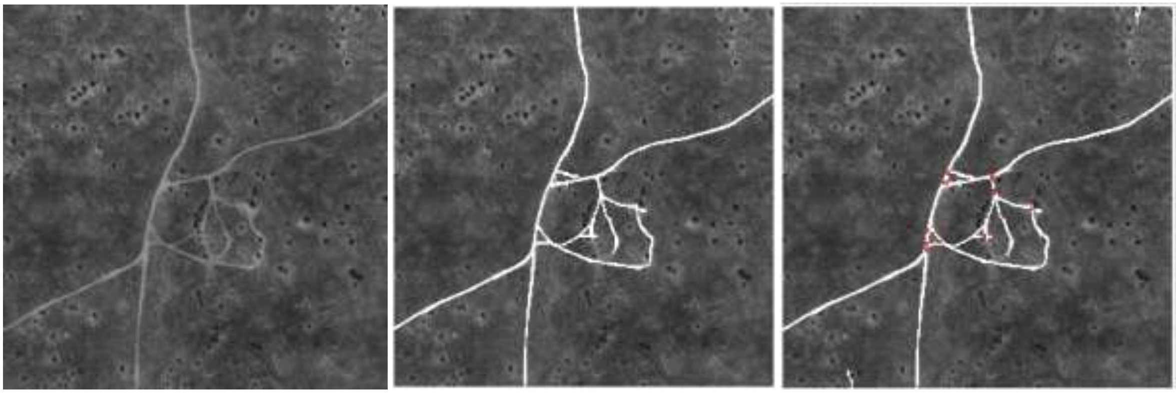

Figure 4a. Test Image 1 Figure 4b. Line Extraction Figure 4c. Extracted Junctions

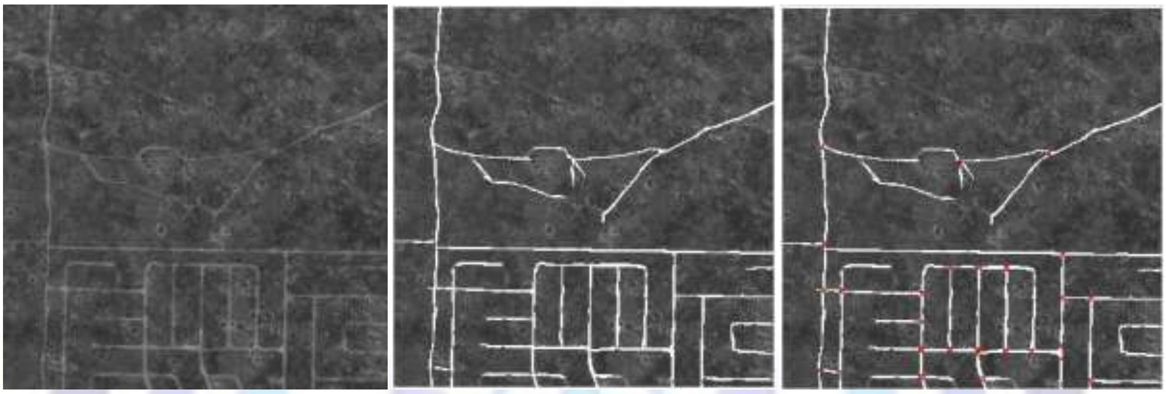

Figure 5a. Test Image 1 Figure 5b. Line Extraction Figure 5c. Extracted Junctions

Another disadvantage of this algorithm is that sometimes a junction is localised twice or thrice at slightly different places near the junction. This is due to the fact that several templates are applied on the image and a junction may satisfy different conditions imposed by the different templates and thus are localised more than once. This occurs most often more X-type junctions. This problem could be solved simply by imposing the condition that more than one junction cannot be found in a 5 x 5 neighbourhood of a pixel which has been labelled as a junction point and that an image cannot contain more than a specified number of junctions. In low-resolution images of size 320 x 320, it is highly unlikely that the number of junctions will be more than fifty.

A last point which need to be mentioned is that the algorithm cannot detect some types of junctions particularly those in which the angle between two of its branches is less than 45o but more than 22.5o. This could be achieved by using the same two masks which we have been using to implement this algorithm. We need only to remove the restriction that we have to choose three non-adjacent arms. However, we need to be careful when removing this restriction. We should not use any three arms otherwise we may end up with a lot of false junctions. Also, the computational cost would increase but this does not matter much in comparison with factors like completeness and correctness. If this is not enough, we can add still more arms but at the cost of increasing computation time.

## V. Conclusion

In this paper, an algorithm for the correct localisation of road junctions from high-resolution aerial images has been presented. We saw that the junction detector has a very high detection accuracy. In most cases, it is well above 90%. In this regard, it is better than many of the solutions already proposed in the literature. However, in order to be useful in autonomous vehicles navigation systems, we need an infallible detector. We believe that the accuracy can be substantially improved by combining the features of several detection methods into a single approach. In our future work, we intend to see how the detector performs in urban or semi-urban regions. At a later stage, the research will focus on the extraction of junctions obtained from images and videos obtained from ground-level images.

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