ARTIFICIAL NEURAL NETWORKS FOR THE DETECTION OF ROAD JUNCTIONS IN AERIAL IMAGES

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ABSTRACT:

Road junctions are important objects for traffic related tasks, vehicle navigation systems, but also have a major role in topographic mapping. The paper describes an approach of automatic junction detection using raster and vector information: mean and standard deviation of gray values, edges as road borders etc. The derived feature set was used to train a feed-forward neural network, which was the base of the junction operator. The operator decides for a running window about having a road junction or not. The found junctions are marked in the output image. The operator was improved by additional features considering parallelism information of roads in junctions. The developed method was tested on black-and-white medium resolution orthoimages of rural areas. The results demonstrate the ability to find road junctions without preliminary road detection.

1. INTRODUCTION

The development of vehicle navigation systems and location based services (LBS) has been accelerated in the last years. For such applications up-to-date, accurate and correct information of the road network is mandatory.

The current acquisition and updating of geospatial information is characterized by a large amount of manual work, and is thus rather costly and slow. Research and development have investigated new and effective solutions. Efforts were focused on different image based automatic solutions as well as the on data collection on the ground.

Automatic road extraction from images has a history of more than two decades. Most early approaches were not very useful, because they only used image processing algorithms such as edge and line detection. Exceptions to these attempts can be found in [1] considering a graph structure for the whole road network, and [2] combining different extractions cues. Wiedemann [3] developed a very sophisticated method based on the Steger line extractor [4]. The Wiedemann-method contains elements from graph theory (e.g. shortest path algorithms) and models the road segments extracted from the images as parts of a complete network. The method has been applied successfully to satellite and medium resolution aerial imagery, and was also implemented for quality control of existing road data, as Willrich has shown on black-and-white orthoimages combined with ATKIS (German Official Topographic and Cartographic Information System) road objects [5]. Other examples of automatic road extraction include e. g. the approaches of Baumgartner [6] for high resolution aerial images, and

Dial et al. for satellite imagery such as those captured with Ikonos or Quickbird [7].

A relatively new technique in digital photogrammetry is the application of artificial neural networks (ANN) for object detection. These networks have proven their universality in several technical fields: Chiu et al. [8] identified several objects with the help of ANN, Tang et al. [9] have reported similar work. Kepuska [10] used a neural network to recognize signalized control points in photogrammetric images, and Abdallah et al. [11] detected airplanes in images with the help of ANN.

The goal of our efforts was to develop a method for road junction detection from medium to high resolution aerial images based on ANN which should be able to deal equally well with three and four arm junctions. The motivation was twofold: firstly, there exists no good road junction detector in the literature without preliminary road detection, probably due to the fact that road junctions have a vastly differing appearance in images, and secondly, we wanted to learn more about ANN. Preliminary results of our work have already been reported in [12] and [14].

2. MODELING ROAD JUNCTIONS

The development of the junction operator called JEANS (Junction Extraction by Artificial Neural network System) started with a model-building step. In this phase image samples of different types of road junctions were collected. The obtained data set contained crossings with different road widths and orientations. In order to somewhat simplify the task the type of the junctions was limited to three and four arm junctions.

In the junction model we have kept the generally used raster information (like mean and standard deviation of gray values), but vector type features were added. Within a given sized window we run an edge detection algorithm (Lanser algorithm [13], which is a rotation invariant version of the Deriche edge operator coupled with a hysteresis threshold, followed by edge smoothing using the Ramer algorithm). Sample results are depicted in Figure 1.
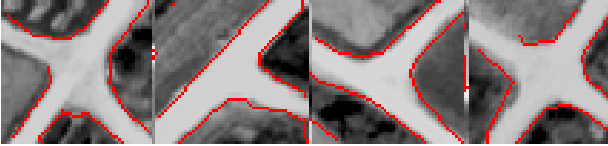

Figure 1. The result of the edge detection

The road junctions have a common feature, which is visible in the derived vectors: most edges run in the direction of the junction. Due to the selected image resolution the junction is not a point-like (zero dimensional) object, and the edges form road borders; the road edges do not cross each other in a single pixel.

To model this finding we use a circle centered around the junction. This circle incorporates the edge evaluation criteria: an edge segment is further investigated if and only if the straight line through this edge segment (called the extended edge) intersects this circle, otherwise it is dropped. Figure 2 shows four junction samples with an adequate sized junction circle.
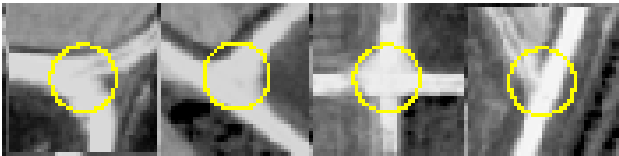

Figure 2. The junction is represented by a centrally placed circle

The edge evaluation is based on the use of the central circle (Figure 3). The circle belongs to a search window, which clips the found edge vectors. All the edge segments in the search window are evaluated by the circle test.
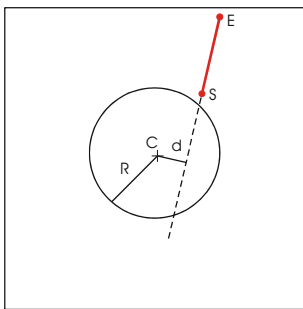

Figure 3. The relation of a found edge to the junction circle

The evaluation itself is carried out by computing the distance d from the center of the circle to the extended edge, where the edge runs from start point S to end point E. The extended edge intersects the circle, if d is smaller the radius R of the circle.

The evaluated and kept edge vectors are possibly road-side segments. Using these vector elements statistical features such as variation of the edge direction or edge length can be derived, which may be specific for road junctions and thus provide the possibility to differentiate junctions from other image features including straight road segments.

Beside this vector based features some raster features – e. g. average and standard deviation values of the gray values – can also be used. The raster data should be collected in a kernel of predefined size within the search window.

The separation of the junctions from the non-junctions is a decision task. The relevant features for this procedure are usually difficult to identify. A small number of features is crucial for the neural network training: the complexity of the network and the training time requirement increases drastically with the number of features as input.

To ease the development step, various combinations of features were analyzed. The evaluation was mainly graphical: pair-wise scatter plots were created with junction–non-junction coloring. The goal of the analysis was to find a set, in which the point clouds of the classes are separated.

The influence of the input features was also investigated by principal component analysis. This tool can help to define the minimum number of adequate features.

The result of the statistical feature analysis was a collection of the most important input features. The set contains the standard deviation of the edge direction and edge length (SDDIR and SDLEN), and the coordinates of the center of gravity of the edge (XS and YS). As raster data the mean intensity value A and its standard deviation SD were kept in the feature set.

The obtained statistical features are used to train the neural networks by adding the information, whether the sample is a junction image or not. The reliability of the correct feature selection was increased by outlier elimination; ambiguous image samples – because of wrong light conditions, occlusions caused by trees, buildings, etc. – were removed. The artificial neural network was thus trained with clean data only.

The junction detection was realized by sliding a window of predefined size over the whole image, similar to a convolution operation. At each step the result of the decision is stored in the center pixel of the window. The result of the operator is a classified image, containing pixels, which are identified as road junctions and those, which are considered as non-road pixels.

3. THE NEURAL NETWORK DEVELOPMENT AND FIRST RESULTS

As mentioned, ANNs have already been used in a few instances in photogrammetry and image analysis. In our method they are applied as sophisticated *pattern classifiers*. The ANN inputs are derived using several image processing techniques, the desired output is thought to be a clear distinction between different patterns, in our case road junction and non-junction patterns.

We have chosen a feed-forward neural network, which is one of the most frequently implemented network types. The network construction comprises an iterative back-propagation training method.

The network has three neuron layers with equally logistic sigmoid processing elements (Figure 4). This neural transfer function has a simple derivative, which is very valuable, since it is allows very fast training. The parameters of the network, which are to be defined during the training, are the weight matrices *IW* and *LW* and bias vectors *b* for all three layers.
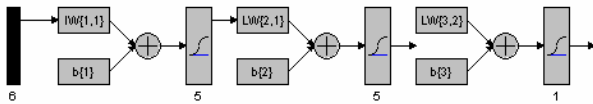

Figure 4. The structure of the applied neural network

The training of neural networks is a time-consuming task. Because of its efficiency the Levenberg-Marquard algorithm [15] was selected. This algorithm uses a learning rule of second order gradient descent with momentum. The momentum helps to avoid the local minima on the error hypersurface. We used the mean square error measure, because it adjusts the network weights and it has moderate performance requirement. The implemented weight update was almost constant, which is achieved by adaptively modifying the optimization step length.

The training set and the network structure were fixed, and an acceptable decision accuracy was searched for changing the number of neurons per layer and using different feature sets. The whole training procedure was controlled by the difference between the required and the obtained network results measured for the training samples. During the training several hundred neural networks were generated, from which the most adequate one was selected in a follow-up evaluation step. Five repetitions with exactly the same structures were used in the network generation to reduce the effect of random initialization.

The developed junction operator was tested on digital black-and-white medium-resolution orthoimages, which cover a region near Frankfurt am Main, Germany. The orthoimages have a pixel size of 0.4 m.

The extracted training samples were image chips with 51×51 pixels, which equals a dimension of 20.4×20.4 m2. Altogether, there were 180 image windows in the training, 1/3 with junctions and 2/3 with non-junctions. 38 image samples were considered to be "ambiguous" and were not further considered (see above).

The kernel size for the raster data acquisition was 7×7 pixels, which equals 2.8×2.8 m^2. The radius of the circle was empirically set of 11 pixels (4.4 m).

Figure 5 shows the results of the evaluation of an image; the junctions in this image were not used in the training. The operator has detected several road junctions. All recognized positions are correct, they are marked with circles. There is an additional potential crossing, marked with a square, where two different collinear road segments are connected.

In addition, there are some pixels on road segments in the image, which are also identified as junctions.
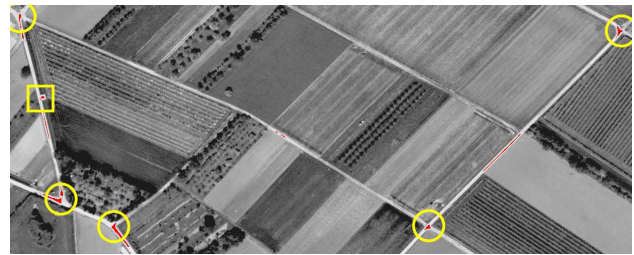

Figure 5. Correctly recognized road junctions (marked with circles) and a position connecting two different collinear road segments (marked with square)

Figure 6 presents a further example of using the junction operator. The correct detections are marked with circles. In this example one can notice the relatively high false alarm rate of the presented approach: many pixels on road segments were labeled as potential junctions (marked in red).

Figure 6. Detected junctions in another part of the study area

4. IMPROVED JUNCTION MODEL

Because of the high false alarm rate of the last test, we modified the basic JEANS algorithm. The first step was a minor modification of the control parameters concerning

the edge detection and the vectorization.

Then the samples for the neural network training were multiplied with rotating the given samples by 90, 180 and 270 degrees, in order to obtain more known training information without extra junction selection. The resulting training set had 542 junction and non-junction samples.

The main change of the improved junction model was the consideration of the parallelism information of the roads. It means, that the road border (the found edges) should be parallel. The edges, which fulfill this requirement, have higher priority in the evaluation and also additional features can be computed considering, that the road body is mainly homogeneous between the borders. The new derived features are: minimum and maximum gray value, minimum and maximum standard deviation, as well as a so-called minimum and maximum quality factor. The latter is a measure for normalized angular difference and normalized length of the overlapping area between the parallels (measure of parallelism).

The derived features were passed into a factor analysis to select the most representative ones. The list containing all input features, namely:

- *XS,YS* (coordinates of the center of gravity of the edges)
- *A7,SD7* (mean gray value and its standard deviation for the central kernel)
- *SUMLEN* (total length of edges running through the central circle)
- *AVELEN*, *SDLEN* (average length of all edges, as well as its standard deviation)
- *SDDIR* (standard deviation of the directions of the edges)
- *QUALMIN,QUALMAX* (quality minimum and maximum for the found parallels)
- *GRAYMIN, GRAYMAX* (minimum and maximum gray values between the parallel edges)
- *STDMIN,STDMAX* (minimum and maximum standard deviation of the above gray values)
- *GRARANGE* (range of the above gray values)

- *STDRANGE* (range of the gray value standard deviations).

The above features were transferred into a factor analysis based on rescaled non-rotated principal components. The analysis was performed both for junction samples (*J=1*) and for non-junction samples (*J=2*). Figure 7 shows the absolute value of the computed factors: *abs(J=1)* and *abs(J=2)*. The third column is the sum of the absolute factors in order to obtain the overall importance.

As one can notice, there were 9 features having a cumulated factor value greater than 3. For the later work only these 9 parameters were kept, which means the new neural network parameters are 3 from the old feature set and 6 from the new one.

The separability of the two categories (junctions and non-junctions) were checked by a linear discriminant analysis. This simple test has shown, that 88.9 % of all 542 samples can be recognized correctly by the use of linear discriminant as decision function. The applied neural network can have better performance because of the more flexible decision boundaries.

After the described improved model building phase the "usual" network series were produced with varied control parameters. The series contained 135 networks with three layers each and different numbers of neurons per layer (from 1 to 7).

Figure 7. The result of the factor analysis for the feature selection
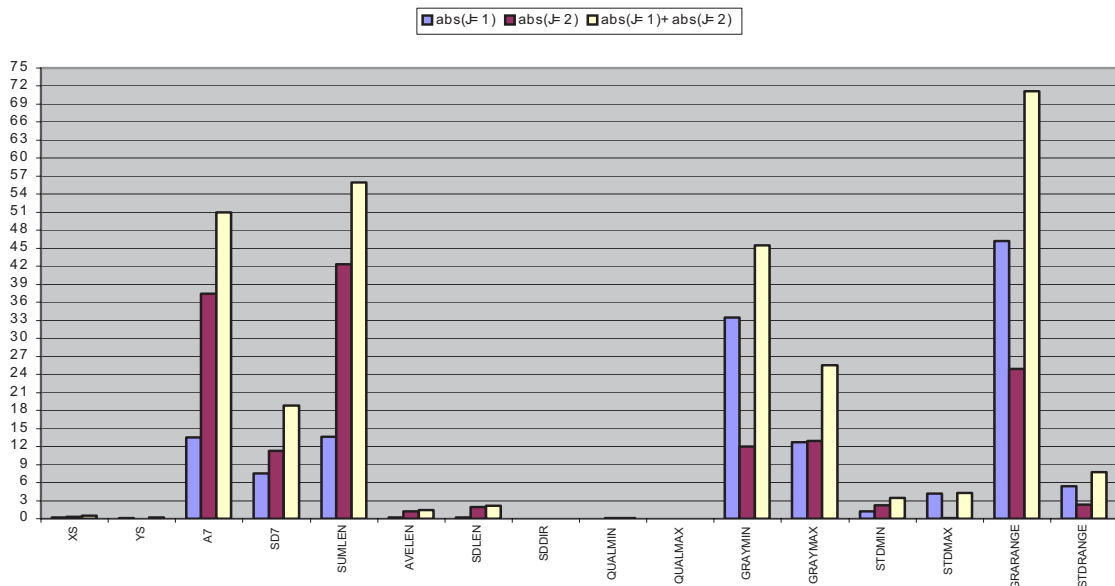
5. RESULTS

The operator was tested on several images. Figure 8 shows a detail of 490 × 352 pixels, containing 11 road junctions. The red marks show detected junction positions, which were slightly enlarged by circular dilation for the better viewing. The operator has found 7 of them (64 %), which are marked with yellow circles. In 4 cases (36 %) the recognition failed: they are marked with yellow rectangles. 6 false recognitions occurred, they are depicted as isolated red blobs..

The second test image had a size of 2935 × 1670 pixels, which contained 20 road junctions (see Figure 9). The correct junction recognition rate was 75 %, which means 15 junctions were detected. 5 junctions were not marked by the operator (25 % error); while about 20 cases were the false alarms.

These wrong positions are probably marked because of the weak differentiation between real road junction and field corners. These errors must be eliminated by additional, more sophisticated algorithms.

Compared to our first version (see section 3) the improved junction operator has a reduced false alarm rate (less pixel marked as junctions, although they aren't), mainly thanks to the parallelism information. The detection accuracy has also increased (compare Figures 10 with Figure 5 and Figure 6).
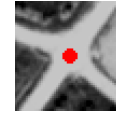

Figure 10. Smaller detected junction position (the point is enlarged by dilation for the better visualization)

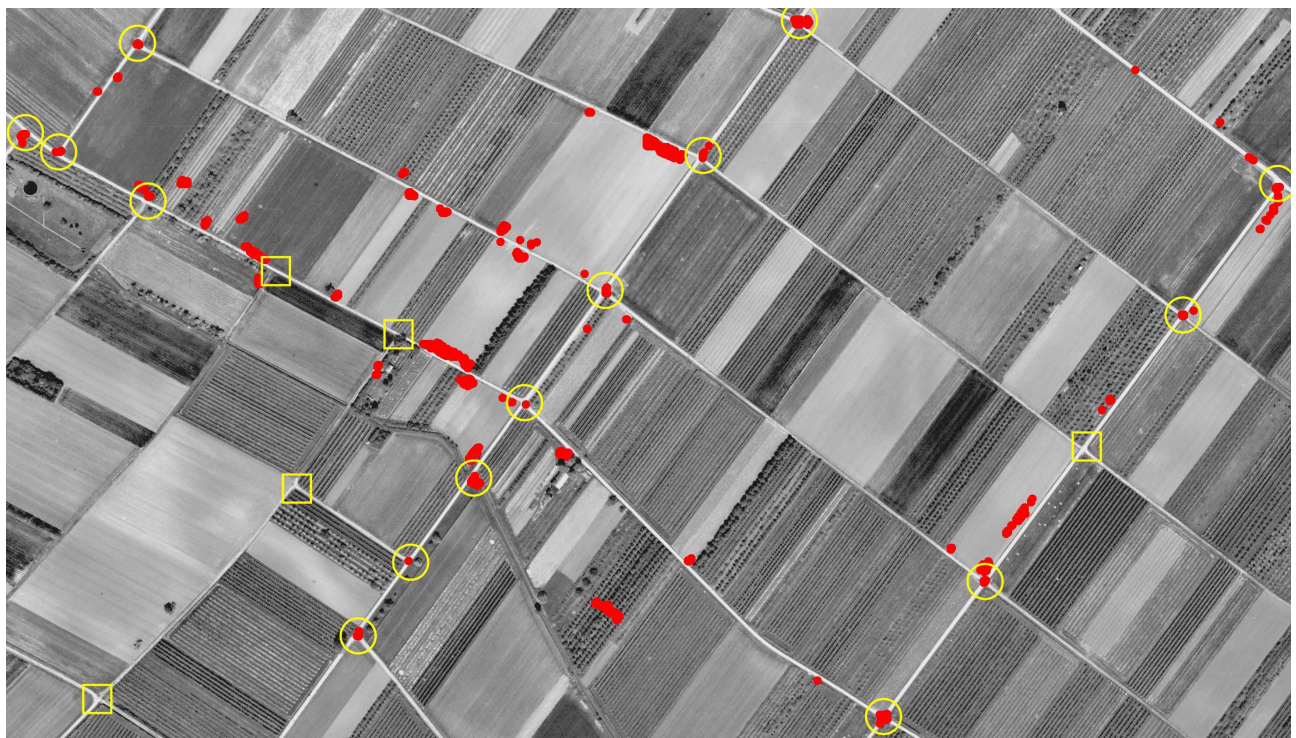Figure 8. Many junctions are detected correctly in this image

Figure 9. Regular junctions are detected correctly in this image, but there are more false detections.

6. CONCLUSION AND OUTLOOK

The experiments have proven the general applicability of the new road junction detector based on integrating raster and vector information in an artificial neural network.

The used vectors are derived by edge detection techniques. Obviously, these techniques do not only find road edges, but also all similar gray level edges all over the image. In order to reduce this ambiguity we have focused on the evaluation of the extracted edges by introducing the central circle criterion. The selected edge vectors were used to derive features, which in conjunction with raster features were the inputs for the artificial neural network.

The presented junction operator currently finds many the pixels, which belong to a road junction. The robustness has been improved by introducing additional rules, like considering the fact that road edges outside the central circle should be parallel, and gray value constancy between these parallel edges.

We hope to improve the results of our work and in particular to further decrease the false alarm rate by introducing a constraint expressing the fact that a road junction must have at least three parallel regions. An additional possibility, popular with ANN, but currently not addressed by our research is the increase of the number of training samples.

Furthermore we hope that the developed algorithm can be integrated into a road extraction system, where the current method supports algorithms, e.g. snake-based road detections. Another possible application of the technique is the quality control of road detection, because the network nodes, the junctions can be detected in an independent way.

Our future plan is the addition of a complex junction description, which is coupled to the detection. The results of such a description are the number of junction arms, the exact direction of the junction roads, their width etc, which have to be transferred into geographic information for car navigation systems.

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