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Automatic Extraction of Traffic Islands from Aerial Images

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Keywords: Road junction, traffic island, level sets, aerial image

Summary: Road junctions are important components of a road network. However, they are usually not explicitly modelled in existing road extraction approaches. In this paper, we consider road junctions as area objects with possible existence of traffic islands in their central area and propose a level set approach for the automatic extraction of islands. A region-based method is employed to initialize the level set function. The junction outline is provided to focus the attention on a specific area and some constraints are introduced to distinguish islands from other features such as cars. The approach was tested using aerial images of 0.1 m ground sampling distance that depict suburban and rural areas. Test results are presented and discussed in this paper.

Zusammenfassung: *Automatische Erfassung von Verkehsinseln aus Luftbildern*. Kreuzungen sind wichtige Komponenten eines Straßennetzes. Sie sind aber in aktuellen Straßenextraktionsansätzen in der Regel nicht explizit modelliert. In diesem Artikel beschreiben wir Kreuzungen als Flächenobjekte und schlagen einen Level-Set-Ansatz für die automatische Extraktion von Verkehrsinseln vor. Eine regionbasierte Methode wird verwendet, um die Level-Set-Funktion zu initialisieren. Die Kreuzungsaußenlinie wird als gegeben angesehen, sie dient dazu, den weiteren Ablauf auf den Kreuzungsbereich selbst zu konzentrieren. Darüber hinaus wurden einige Bedingungen eingeführt, um Verkehrsinseln von anderen Objekten wie Autos zu unterscheiden. Der Ansatz wurde anhand mehrerer Luftbilder mit einer Bodenauflösung von 0,1 m, die suburbane und ländliche Gebiete zeigen, getestet. Die Testergebnisse werden präsentiert und ausführlich diskutiert.

1 Introduction

Geospatial databases contain various man-made objects among which roads are of special importance as they are used in a variety of applications such as car navigation. Road junctions are important components of a road network. However, they are usually not explicitly modelled in existing road extraction approaches. Road junctions in road network extraction systems have mainly been modelled as point objects at which three or more road segments meet (Gerke 2006, Zhang 2004, Barsi et al. 2002, Wiedemann 2002, Hinz et al. 1999, Heipke et al. 1995). In contrast, in Gautama et al. (2004), Laptev et al. (2000) and Mayer et al. (1998), junctions are treated as planar objects. This kind of modelling does not always reflect the required degree of detail obtainable in high resolution aerial images (cf. Fig. 1). A more detailed modelling of road junction is necessary for data acquisition in large scales.

In Heipke et al. (1995), a strategy to extract roads in two different scales is proposed. In the fine resolution, roads are modelled as area objects and in coarse resolution as line objects. Results from both resolutions are merged using a rule based system. To delineate the junction area, segments next to accepted road segments are recursively investigated for homogeneity of the adjacent area. Laptev et al. (2000) and Mayer et al. (1998) employ a snake model to delineate junctions, and Gautama et al.

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(2004) use a differential ridge detector in combination with a region growing operator to detect junctions.

However, none of the described approaches tried to model traffic islands, which often are present in the central area of junctions. Traffic islands are important componenets in traffic management and car navigation systems. In particular, future car navigation systems require detailed and accurate topographic information. Therefore, traffic islands should be included in a detailed topographic database. Since some junctions contain islands in their centre, a detailed junction model needs to consider the possible existence of small islands.

A road junction can contain several small islands located in its central area. The number of islands varies in different junctions depending on the number of crossing roads and the functionality of the junction. Traffic islands may be of diverse geometrical shape. Furthermore, they may be partially occluded by shadows from traffic lights, traffic signs, vehicles and trees. These properties imply that the extraction of islands is a challenging problem of aerial image analysis.

In this paper, we attempt to model traffic islands in rural and suburban areas and use a method based on level sets for their automatic extraction. The junction outline is used as input to focus the attention on a limited area. Furthermore, some geometric and topological constraints are defined to distinguish islands from other features. In Section 2 a short review of level sets is given. The individual steps of the proposed strategy are described in Section 3. In Section 4, results using aerial grey level imagery of 0.1 m ground sampling distance are presented and evaluated. The paper concludes with a discussion of the reached state and an outlook for future work.

Fig. 1: Superimposition of vector data on a high resolution aerial image.

2 Level Sets

Level sets share many properties with snakes. *Snakes* (Kass et al. 1988) have emerged as a powerful tool for semi-automated object modeling. They are especially useful for delineating objects like traffic islands that are difficult to model with rigid geometric primitives. Snakes are represented as explicit, parametric contours. As a result, they do not allow for automatic changes of topology. Thus, the simultaneous extraction of a priori unknown number of objects, which require such a change of topology during the extraction process, is not straightforward. Several approaches were proposed to address this problem (McInerney & Terzopoulos 1995, Szeliski et al. 1993). They proposed heuristic procedures for detecting possible splitting and merging of the initial contour. In contrast, *level sets* (Osher & Sethian 1988) allow for splitting and merging in a natural way and are thus more suited to solve our problem.

The core idea of level sets is to implicitly represent a contour C as the zero level curve of a function ϕ of higher dimension. Such an implicit representation allows for the de-

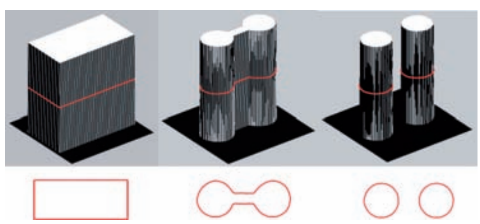


Fig. 2: Natural change of topology in the level set framework. The top row presents the evolution of the embedding function ϕ over three iterations and the zero level curve C (red line); the bottom row shows a 2D representation of C.

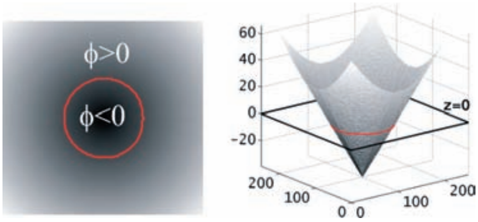


Fig. 3: Illustrating level sets. (a) The curve C (red) is used to construct the level set function ϕ such that ϕ is negative inside and positive outside the curve. Distance values d are grey value coded. (b) A plane at zero level ($Z = 0$) intersects the level set function ϕ, and thus the zero level curve C is obtained.

sired topological changes of the contour during the evolution of the level set function ϕ (cf. Fig. 2).

An initialisation of ϕcan be constructed in the following way: Let C be a closed curve representing the boundary between two regions, one region inside the curve and another region outside the curve. ϕ is then defined as the signed distance $\pm d(x)$ to the curve, negative inside and positive outside (cf. Fig. 3 a & b).

The definition is illustrated:

$$\phi(x) = \begin{cases} -d(x) & \text{if } x \text{ is inside } C \\ +d(x) & \text{if } x \text{ is outside } C \end{cases} \tag{1}$$

While the use of the distance $d(x)$ is not mandatory when using level sets, it assures that ϕ does not become too flat or too steep near C and subsequently can be differentiated across the zero level curve without running into numerical problems.

In order to combine the characteristics of the level set function and the image information, an energy functional consisting of an internal energy term (smoothness term) and an external energy term (data term) can be set up and consequently minimised using the calculus of variations, similar to the approach used for snakes. The internal energy term penalizes the deviation of the level set function from a signed distance function, whereas the external energy term drives the motion of the zero level curve to the desired image features such as an object boundary.

In this paper, we use a level set formulation that forces the level set function to be close to a signed distance function throughout the evolution. It was shown that a signed distance function must satisfy the property of $|\nabla\phi| = 1$ (Osher & Fedkiw 2002). Therefore, the following formula was proposed as the internal energy term (Li et al. 2005):

$$P(\phi) = \int_\Omega \frac{1}{2}(|\nabla\phi| - 1)^2\, dx\, dy \tag{2}$$

$P(\phi)$ is a metric to characterize how close a function ϕ is to a signed distance function in a specified computational domain $\Omega \subset R^2$.

In order to derive the external energy let I be an image, and g be the *edge indicator function* defined by

$$g = \frac{1}{1 + |\nabla G_\sigma * I|^2} \tag{3}$$

where G_σ is the Gaussian kernel with standard deviation σ, and ∇ denotes the gradient operator. Thus, in image areas with large gradients g is small and vice versa. The external energy $E_m(\phi)$ can then be defined as

$$E_m(\phi) = \lambda\, L_g(\phi) + v\, A_g(\phi) \tag{4}$$

where $\lambda > 0$ and v is a constant.

$L_g(\phi)$ is a length term obtained by taking the *surface integral* (line in R^2) of the function g over the curve C:

$$L_g(\phi) = \int_\Omega g\, \delta(\phi)\, |\nabla\phi|\, dx\, dy \tag{5}$$

where δ denotes the univariate Dirac delta function. It can be thought of as a function which is zero everywhere except at the origin, where it is infinity.

$$\delta(\phi) = \begin{cases} \infty & \text{if } \phi = 0 \\ 0 & \text{if } \phi \neq 0 \end{cases} \tag{6}$$

Since $\delta(\phi) = 0$ almost everywhere except at the zero level curve C, the energy functional $L_g(\phi)$ measures the total effect of g over the curve C. Thus, $L_g(\phi)$ is small if also g is small, which is the case near the areas with a large image gradient (see Eq. 3).

$A_g(\phi)$ is an area term obtained by computing the *volume integral* (area in R^2) of g over the interior region $\Omega_\phi^- = \{(x, y) < 0\}$ (OSHER & FEDKIW 2002):

$$A_g(\phi) = \int_\Omega g H(-\phi)\, dx\, dy \tag{7}$$

where H is the Heaviside function. The Heaviside function is a discontinuous function whose value is zero for a negative argument and one for a positive argument

$$H(\phi) = \begin{cases} 0 & \text{if } \phi < 0 \\ 1 & \text{if } \phi \geq 0 \end{cases} \tag{8}$$

The energy functional $A_g(\phi)$ in Eq. 7 is introduced to speed up curve evolution (LI et al. 2005). Note that when g is constant ($g = 1$), the energy functional in Eq. 8 equals the area of the region Ω_ϕ^-, and as g gets smaller, so does $A_g(\phi)$.

The external energy is then defined as

$$E_m(\phi) = \lambda\, L_g(\phi) + v A_g(\phi) \tag{9}$$

where $\lambda > 0$ and v is a constant.

Now, the following total energy functional is defined

$$\begin{aligned} E(\phi) &= \mu\, P(\phi) + E_m(\phi) \\ &= \mu \int_\Omega \frac{1}{2} (|\nabla \phi| - 1)^2\, dx\, dy \\ &\quad + \lambda \int_\Omega g d(\phi) |\nabla \phi|\, dx\, dy \\ &\quad + v \int_\Omega g H(-\phi)\, dx\, dy \end{aligned} \tag{10}$$

The external energy E_m drives the zero level curve toward the object boundaries, while the internal energy $P(\phi)$ penalizes the deviation of ϕ from a signed distance function during its evolution, and $\mu > 0$ is a parameter controlling the effect of penalisation.

Eq. 10 is solved using the *calculus of variation* (COURANT & HILBERT 1953). The Gateaux derivative (first variation) of the functional E in Eq. 10 can be written as

$$\begin{aligned} \frac{\partial E}{\partial \phi} &= -\mu \left[\Delta \phi - \operatorname{div}\left(\frac{\nabla \phi}{|\nabla \phi|} \right) \right] \\ &\quad - \lambda \delta(\phi) \operatorname{div}\left(g \frac{\nabla \phi}{|\nabla \phi|} \right) - v g \delta(\phi) \\ &= 0 \end{aligned} \tag{11}$$

where Δ is the Laplacian operator. Eq. 11 is transferred into time space by taking the temporal partial derivative of the level set function $\frac{\partial \phi}{\partial t}$ and solved iteratively by applying the method of steepest descent (LI et al. 2005):

$$\begin{aligned} \frac{\partial \phi}{\partial t} &= \mu \left[\Delta \phi - \operatorname{div}\left(\frac{\nabla \phi}{|\nabla \phi|} \right) \right] \\ &\quad + \lambda \delta(\phi) \operatorname{div}\left(g \frac{\nabla \phi}{|\nabla \phi|} \right) + v g \delta(\phi) \end{aligned} \tag{12}$$

Eq. 12 is the evolution equation of the level set function used in our approach. The iterations stop when the change of ϕ becomes smaller than a pre-defined threshold.

3 Extraction Strategy

In order to focus the extraction of traffic islands to the proper image regions, we make use of the junction outlines as prior information (see RAVANBAKHSH et al. 2008 for a description of how we detect these outlines). Here, the outlines together with the aerial imagery are regarded as input. Our strategy comprises three steps (cf. Fig. 4). First, the intended image area is segmented. Next, initialization of the level set function is carried out followed by the curve evolution. Finally, islands are selected by introducing some additional constraints. The obtained result consists of the extracted islands.

3.1 *Segmentation*

First, the image area in which islands are located is clipped from the image. The search space for islands is further restricted to an area around the estimated junction centre point called *island area* (cf. Fig. 5 a). To begin the island extraction by curve evolution, the initial level set function needs to be constructed. It is computed within the island area. Prior segmentation of this area is carried out to derive a rough idea of island regions from which the initial level set function is constructed. Skipping the segmentation step results in a much larger number

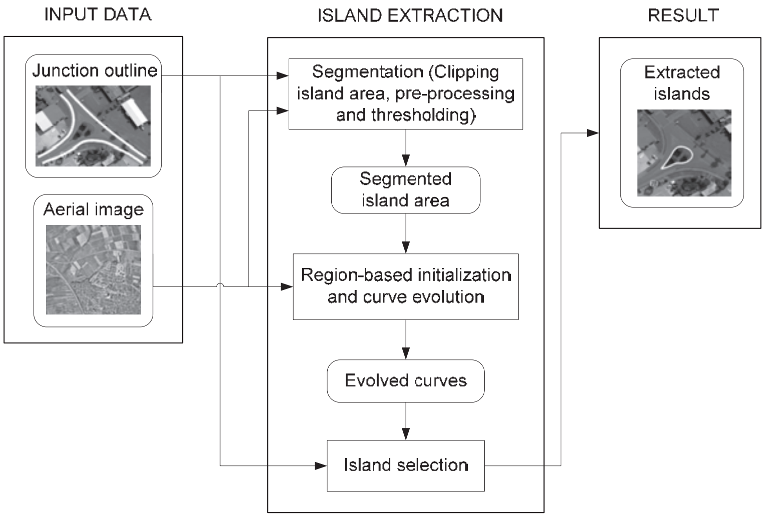


Fig. 4: Workflow of island extraction.

of iterations, furthermore, many undesirable features can be delineated when the evolving curve moves towards the islands.

Since we work in suburban or rural regions we assume that most of the junction area shows a rather homogeneous grey value distribution. This assumption is equivalent to expecting that there are not too many disturbances such as cars or shadows in the junction. Under these circumstances, the histogram of the pre-procesed image shows one main peak which is related to the surface material of the road and potentially a few smaller peaks related to the islands and various disturbances (cf. Fig. 6). To start pre-processing morphological opening is applied in order to remove distortions such as road markings. Subsequently, closing with the same structuring element is performed to eliminate small shadows etc. Next, Gaussian smoothing is applied to the image (cf. Fig. 5b) followed by thresholding the histogram (cf. Fig. 5c). The threshold value is computed by applying the Iterative Self-Organizing Data Analysis Technique Algorithm (ISODATA – Ridler & Calvard 1978) on the histogram of the island area. At this stage, we consider convex areas inside the junction to be potential islands.

3.2 *Initialization and Curve Evolution*

The initial level set function is constructed from the segmented image so that areas in white are assigned a negative value and black areas take a positive value of the same magnitude. The zero level curve of the initial level set function is shown in Fig. 5d. To evolve towards the island boundaries, the coefficient of the weight v of the area term

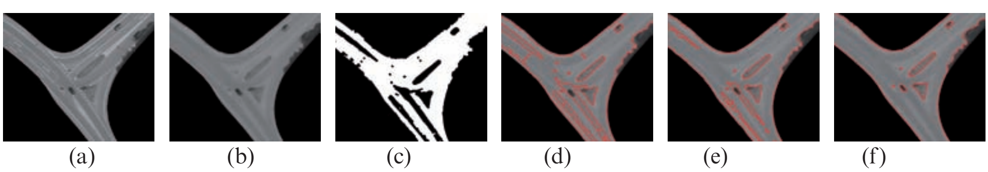


Fig. 5: (a) Island area. (b) pre-processed image. (c) Segmented image. (d) The zero level curve of the corresponding initial level set function. (e) Intermediate result of the zero level curve evolution with $\lambda = 4$, $\mu = 0.13$, $v = 1.5$ after 50 iterations. (c) The zero level curve of the final level set function after 265 iterations.

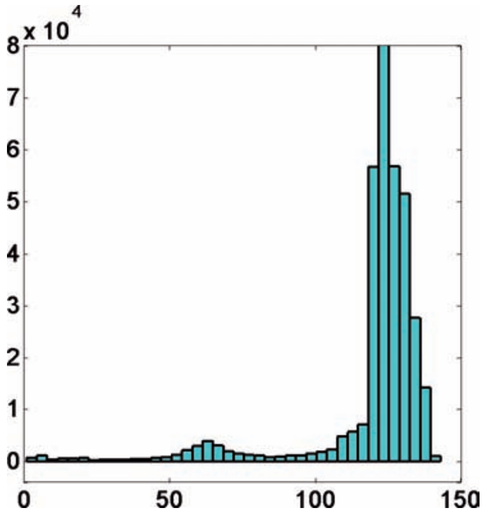


Fig. 6: Grey value histogram of the pre-processed island area with one large peak belonging to the road surface area. In this example a threshold of 121 was computed for segmentation, and the islands are darker that the road surface area.

in Eq. 4 needs to be positive if the island surface is brighter than the surrounding surface area, and negative otherwise. The question of whether the island surface is brighter or darker than the surroundings is derived by analysing the histogram of the pre-processed island area (see Section 3.1 and Fig. 6). In examples where among existing islands some are darker and some others are brighter than the background, only the group of islands with the larger number of pixels can be detected with our method.

The initial level set function then evolves according to the evolution equation (12). Figs. 5e&f present an example in which the zero level curve converges to the boundary of the islands.

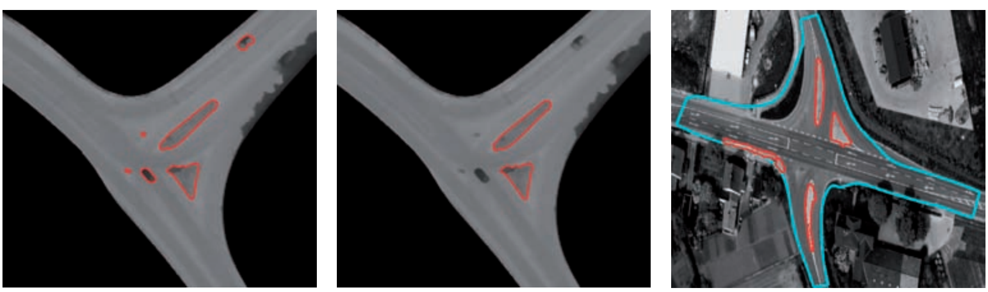
3.3 *Island Selection*

In order to select the final islands, some geometric and topological constraints are introduced based on the properties of islands, because, in addition to the islands, some undesirable features such as vehicles and large shadow areas may have been extracted as island candidates. Small closed areas below a certain size are removed. Since island candidates must be located within the junction outline, those curves that touch the junction outline are also removed. Fig. 7 shows the individual steps of island selection.

Finally, islands possess boundaries with a small curvature variation, so the contours with high curvature variations, i. e. their mean curvature is greater than a certain threshold, are eliminated.

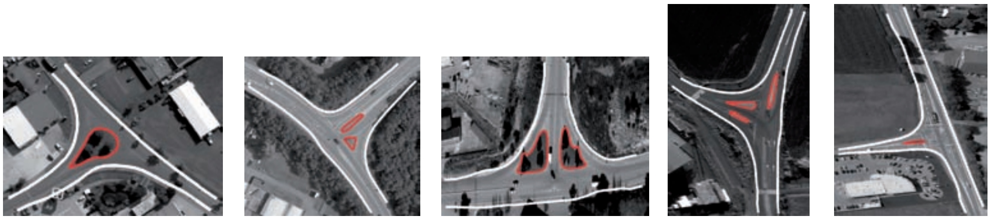
4 Results and Evaluation

For our experiments, we used black-and-white aerial Digital Mapping Camera (DMC) orthoimagery with a ground sample distance of 0.1 m. The images depict rural and suburban areas. Because the number of junctions including traffic islands in one scene is generally low, junctions are selected from a large number of images. We tested



(a) (b) (c)

Fig. 7: (a) Closed curves are retained as island candidates. (b) Two cars having areas of 13 and 11 m^2 are eliminated. The remaining islands have areas of 67 and 52 m^2. (c) shows the topological constraint. One of the obtained contours (left side) partly touches the junction outline and is removed.



(a) (b) (c) (d) (e)

Fig. 8: Road junction extraction results. Image samples represent scenes that contain varying degrees of complexity including disturbances.

the proposed approach on a set of road junction samples with an identical set of control parameters for the level sets. Altogether 17 islands were processed. Some selected samples are given in this Section to demonstrate the capabilities of the new approach (cf. Fig. 8).

In order to quantitatively evaluate the performance of the approach, we compared the extraction results to manually plotted islands used as reference data. The comparison was carried out by matching the extraction results to the reference data using the so-called buffer method (HEIPKE et al. 1998). An extracted object is assumed to be correct if the maximum distance between the extracted object and its corresponding reference does not exceed the buffer width. Furthermore, a reference object is assumed to be matched if the maximum deviation from the extracted object is within the buffer width. Based on these assumptions the following quality measures were used in our work:

- Completeness: is the ratio of the number of matched reference objects to the number of reference objects.
- Correctness: is the ratio of the number of correctly extracted objects to the number of extracted objects.
- Geometric accuracy: is the average distance between the correctly extracted objects and its corresponding reference expressed as root mean square (RMS) value.

Tab. 1 shows the evaluation results of the island extraction. The buffer width can be defined according to the required extraction accuracy for a specific application. In our tests, it was set to 0.3 m and 0.5 m, i. e. 3 pixels and 5 pixels in concert with the image resolution of 0.1 m. This selection allows to assess the relevance of the approach for applications that demand varying degrees of accuracy.

Tab. 1: Evaluation results for traffic islands.

Buffer width (m)	0.3	0.5
Reference number of islands	17	17
Completeness	65 %	71 %
Correctness	60 %	87 %
Geometric accuracy (m)	0.18	0.22

As expected, while the results are encouraging, because a number of islands could be extracted correctly and accurately, a few problems still remained. Also, we would like to emphasize that the percentages given in Tab. 1 have to be considered with some care, since they are not based on a very large number of cases. Nevertheless, the table shows that the developed approach is in principle capable of extracting traffic island form high resolution aerial images in rural and suburban areas.

A closer look to the results revealed that among the 17 traffic islands, two could not be detected for two reasons:

- In the first case the island was very narrow. As a result, morphological operations applied in the segmentation step, caused the size of the island to decrease and consequently the narrow parts of the island were almost washed out (cf. Fig. 9 a).

(a) (b) (c) (d) (e)

Fig. 9: Illustrating different problems in the detection of islands. (a) The bottom island cannot be extracted because it is very narrow. (b) Original image with a poor contrast at the island border. (c) The island is almost wiped out after pre-processing. (d) Tree shadows affecting the final result. (e) Shadows from the traffic sign causing the final curve to lie slightly ouside the correct island boundary.

- Poor contrast between the island surface and the surrounding area caused another island to be nearly washed out during preprocessing. Thus, it could not be detected in the following steps (cf. Fig. 9b&c).

Likely disturbances, which deteriorate the geometrical accuracy of the island detection are of two kinds: shadows of trees situated inside the islands (cf. Fig. 9d) and vehicles and traffic signs beside the islands and their shadows (cf. Fig. 9e). In these cases the level set method delivered results of geometrically somewhat reduced quality, however, the islands themselves could be extracted.

5 Conclusion and Outlook

In this paper, we have proposed a new approach for the automatic extraction of traffic islands often appearing in the central area of junctions, which is based on a level set formulation. Level sets were primarily chosen because of their adaptive topology. While the presented results indicate some problems with the developed method, they also demonstrate the feasibility of extracting traffic islands using level sets from black and white high resolution aerial images, since 15 out of 17 islands were extracted, and the correctness of the extracted areas amounted to 87%. Nevertheless, partial occlusion of islands by shadows (cf. Fig. 9d) as well as poor contrast on the island boundaries (cf. Fig. 9b) cannot be overcome at this stage.

There are several possibilities to further enhance the results obtained so far and to be able to deal with more complex scenes. The incorporation of high-level prior knowledge about the shape of traffic islands within the level set framework can provide a solution to these problems. In the literature, there are some references of successful object extraction using shape information in the presence of image noise, clutter and occlusions (Cremers et al. 2006, Bailloeul et al. 2005, Cremers et al. 2003). Furthermore, such shape-driven level set schemes can reduce the number of detected island candiates that are obtained at the evolution stage.

Due to a veriety of disturbing features in urban areas such as large shadows and a potentially high number of vehicles inside the junction, the segmentation may fail to provide meaningful initial results for starting the curve evolution. In such cases, prior detection and removal of theses features seems to be necessary to obtain a proper segmentation result. Detection of disturbing features as well as islands of different radiometric characteristics in a junction can be performed using a multiple level set framework (Vese & Chan 2002). However, having initially several classes of features can add to the complexity of the problem. The use of other data sources such as precise height data and multispectral images can be of help to remove irrelevant classes of features.

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