ROAD JUNCTION EXTRACTION FROM HIGH RESOLUTION AERIAL IMAGES

M. Ravanbakhsh, C. Heipke, K. Pakzad

Institute für Photogrammetrie und GeoInformation, Leibniz Universität Hannover
Nienburger Str. 1, D-30167 Hannover, Germany
[ravanbakhsh, heipke, pakzad]@ipi.uni-hannover.de

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ABSTRACT:

Road junctions are important components of a road network. However, they are usually not explicitly modelled in existing road extraction approaches. In this research, we model road junctions in detail as area objects and propose a methodology for their automatic extraction through the use of an existing geospatial database. Prior knowledge derived from the geospatial database is used to facilitate the extraction. We propose a new approach called GVF Ziplock snake that integrates the GVF (Gradient Vector Flow) field as an external force field into a Ziplock snake in order to delineate the junction border. Road extraction results provide fixed boundary conditions for the proposed snake. The approach was tested using Digital Mapping Camera (DMC) images of 0.1 m ground resolution taken from suburban and rural areas. Extraction results are represented in order to illustrate different steps of the method and to prove its feasibility.

1. INTRODUCTION

The need for accurate geospatial databases and their automatic updating is increasing rapidly. 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, transport and fire services. As their extraction from images is costly and time-consuming, automation is seen as a promising solution to this delimma. However, data acquisition is difficult to automate. The problem for automatic data extraction lies mostly in the complex content of aerial images. To ease the automation of an image interpretation task, prior information can be used (Gerke, 2006), (Boichis et al., 2000), (Boichis et al., 1998), (De Gunst, 1996). This often includes data from an external geospatial database. Road junctions are important components of a road network and if modeled accurately can improve the quality of road network extraction (Boichis et al., 1998). However, there are only few approaches which are dedicated to this task. Junctions are mainly extracted in the context of automatic road extraction. Most of the existing approaches initially concentrate on road extraction to create the road network. Subsequently the extraction of road junctions is realized by perceptual grouping of road hypotheses. In such approaches, junctions are regarded as a point object (Zhang, 2003), (Wiedemann, 2002), (Hinz, 1999). In contrast, in (Gautama et al., 2004) and (Mayer et al., 1998) junctions are treated as planar objects. In (Gautama, 2004) a differential ridge detector in combination with a region growing operator is used to detect junctions and in (Mayer et al., 1998) a snake model is used to delineate junctions. There are also some methods which exclusively deal with junctions. (Barsi et al., 2002) present a road junction operator developed for high-resolution black-and-white images. The operator uses a feed-forward neural network applied to a running window to decide whether it contains a road junction. The drawback of the system is the high level of false alarms. (Wiedemann, 2002) uses a method to improve the quality of the junction extraction which resulted from the approach presented in (Hinz et al., 1999). In (Wiedemann, 2002), several internal and external

evaluation measures are used for the combination of connected roads. The solution with the largest evaluation score is regarded as the solution for the junction.

In (Boichis et al., 2000) and (Boichis et al., 1998) a knowledge based system for the extraction of road junctions is presented. Junctions are classified into four classes and each class is modeled separately. The information derived from an external database is used to generate hypotheses for the junction shape and for main and secondary roads. A drawback of this approach is that image information is not exploited for the formation of main and secondary roads. In (Teoh and Sowmya, 2000) junctions are recognized by using several rules and a supervised learning method. They are classified into several types and each type is treated individually. Rules address several attributes of the junctions. The range of values for the attributes comes from a large set of data. Since the result of the approach is not available in publications, its performance cannot be assessed.

Road junctions in road network extraction systems have mainly been modeled as point objects at which three or more road segments meet (Zhang, 2003), (Wiedemann, 2002), (Hinz, 1999). The junction position in such systems is computed by simple extension of neighboring road segments. This kind of modeling does not always reflect the required degree of detail. In Fig.1, vector data is superimposed on a sample image to describe the problem. In the given image resolution, the junction centre covers an area, so it should be considered as an area object. Thus, a detailed modeling of junctions is needed for data acquisition purposes in large scales. In this paper, junctions are modeled in detail as area objects. The approach uses an existing geospatial database and leads to the extraction of refined road junction data. In section 2, a short overview of the proposed strategy is given. In section 3 junctions are classified and modeled. Various steps of the proposed strategy are described in section 4. Some results of the road junction extraction are shown and discussed in section 5. In section 6, an outlook for future research is given.

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

2. OVERVIEW OF THE APPROACH

We used Digital Mapping Camera (DMC) images with a ground resolution of 0.1 m. The images were taken over rural and suburban areas. Besides the image, the German ATKIS (Amtliches Topographisch-Kartographisches Information System) with a content approximately equivalent to that of 1:25000 scale topographic maps is entered into the system as part of the input data. In ATKIS, the planimetric accuracy for a road object is defined as ± 3m.

Three main parts of our approach are introduced (Fig. 2):

- Pre-analysis of geospatial database
- Extraction of road arms
- Road junction reconstruction

In the first part, the geospatial database is analyzed resulting in a rough idea of the junction appearance in the image. In the second part, road arms are extracted within a limited area around the initial junction position with a size of 70*70 m^2 (700*700 pixels). A road arm is the longest straight road segment connected to the junction center. In the third part, the road junction is reconstructed using a snake-based approach that integrates the Gradient Vector Flow (GVF) (Xu and Prince, 1997) as an external force field into a Ziplock snake

(Neuenschwander et al., 1997) in order to delineate the junction border.

3. MODEL

3.1 Road junction classification

For traffic safety, different kinds of junctions have been designed. Different types of junctions have different properties and construction specifications. In our work, junctions have been classified with an emphasis on the most common features among them. We classified junctions into four main classes: simple, complex, roundabout and motorway. Simple junctions contain three or more road arms without islands in the center. In contrast, complex junctions do contain islands in the center. A road model for simple junctions complies with the classic road model in which roads are defined as quadrilateral objects with parallel edges and a constant width. In three other classes, roads do not necessarily follow this classic model because there might be, for instance, roads with a changing width. The main difference between motorway junctions and others is that crossing roads are not at the same height. In other words, roundabouts, simple and complex junctions are defined in two dimensional space but motorway junctions are defined in three dimensional space. In complex junctions, connected roads enclose an area in which islands are located despite the roundabout whose roads intersect its large circular island. In this paper, we focus on simple junctions only.

3.2 Road junction model

The conceptual model of simple road junctions is represented and described in Fig. 3. According to the model, a junction area is composed of two parts: the junction itself and the road arms. The junction, where road arms are connected, is composed of the junction border at its central area. A road arm is defined in terms of geometry and radiometry as following:
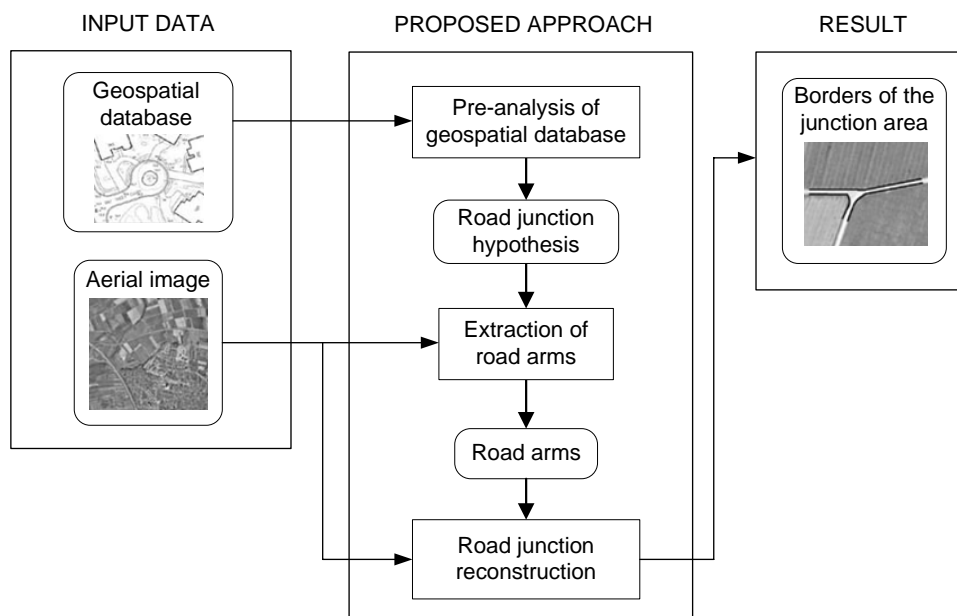

Figure 2. Proposed system organisation

- Geometry: A road arm is a rectilinear object which is represented as a ribbon with a constant width and two parallel road edges.
- Radiometry: A road arm is considered to be a homogeneous region with high contrast to its surroundings. The absolute brightness depends on the surface material.

Disturbances such as occlusions and shadows are not explicitly included in the model at this stage.
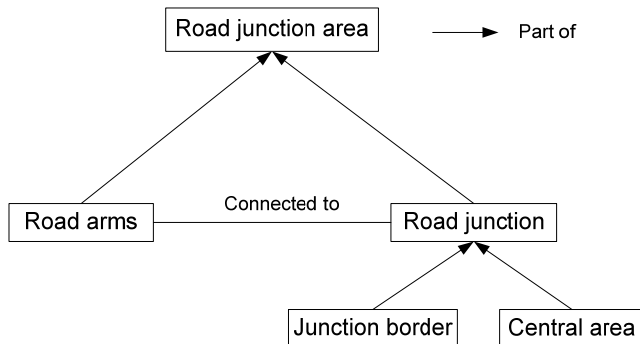

Figure 3. Road junction model

4. EXTRACTION STRATEGY

The strategy guides the system where and how to extract objects in image space and how to interpret extracted elements (De Gunst, 1996) (Fig. 2). In this work, we make use of prior knowledge derived from a geospatial database to extract only those parts of the object which are consistent with the corresponding content of the geospatial database. As mentioned above our strategy consists of three steps.

4.1 Pre-analysis of geospatial data base

The geospatial database we used contains explicit geometric and implicit topologic information about road junctions. Topologic information determines the number of roads connected to the junction centre and geometric information provides us with the approximate location of the junction and the width of the connected roads. A road junction in the geospatial database is composed of a centre point at which a

few lines or polylines meet. Using vector coordinates of lines, we compute road directions. In the road extraction step, geometric and topologic information are used to construct road segments.

4.2 Extraction of road arms

Roads can be bent in different ways, for instance, in a simple curved form, serpentine curve or in a state with changing width. However, in the area close to the junction centre they are mainly straight because of traffic safety regulations. This fact leads us to extract long and straight road segments near the junction centre. They are called road arms (Fig. 4). To illustrate various steps and show the result of each one, we used some image samples. In order to apply the geometric part of the road model, edges are extracted from the image using the Deriche edge detector. Subsequently, a thinning operation is applied, yielding one pixel wide edges. The edges are approximated by polygons to facilitate further processing. We call the result of this step edge segments. Edge segment parameters like image coordinates of endpoints, length and direction are computed. These parameters are used later for the road segment construction. We then group edge segments based on the direction of connected roads from the geospatial database. The number of groups corresponds to the number of connected roads (Fig. 5-a). Since road directions derived from the geospatial database are regarded as reference directions, each group should contain parallel edge segments having a direction similar to their reference direction. It is noted that the direction difference between edge segments in each group must be below a predefined threshold, 15 degrees. Next, as a part of the geometric road model, width and the width constancy between two edge segment candidates are checked. A prerequisite for this step is that two candidates must overlap and must have opposite directions (anti-parallelism condition). Next, radiometric properties of the resulting road segments are investigated. According to the radiometric road model, the area between two road edges should be bright and homogeneous. This means the mean gray value within each area must fall into a predefined range and its variance must be smaller than a predefined threshold. Resulting road segments are verified by extracting road centerlines from an image of reduced resolution (Heipke et al., 1995) (Fig. 5-b).
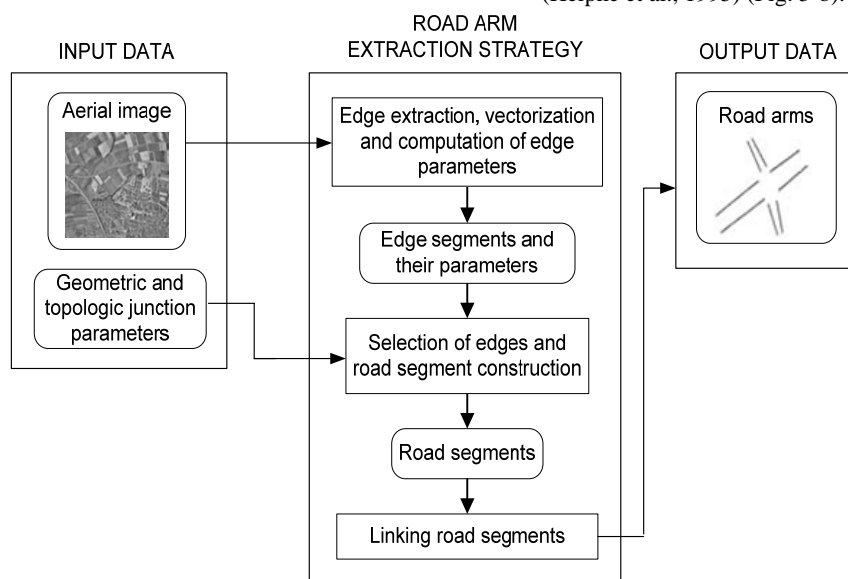

Figure 4. Road arm extraction

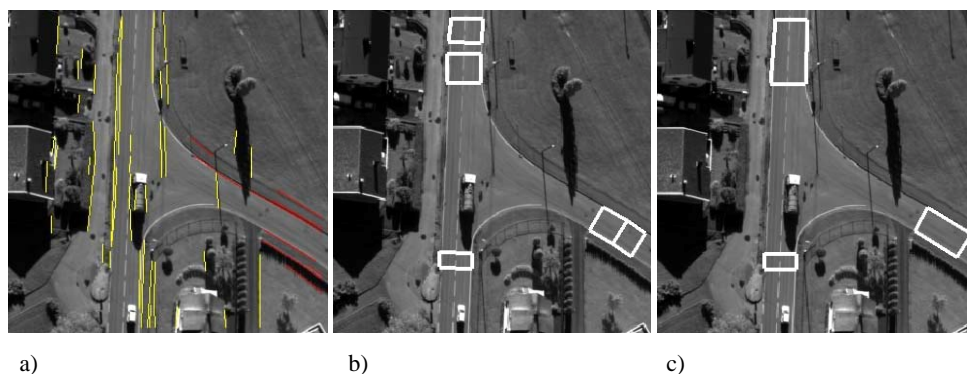a)   b)   c)

Figure 5. (a) illustrates two groups of edge segments in red and yellow. Yellow edge segments contain two groups since related roads are collinear. (b) shows the resulting road segments. (c) shows the extracted road arms.

Although we have so far extracted groups of road segments, what is needed is one road arm per group. To achieve this purpose, road segments within each group are linked (Fig. 5-c). Next, the orientation of each resulting road arm is investigated with the aim to decide which end point faces the junction. This information could be taken from the geospatial data base, but in order to be more independent of the geometric accuracy of the database, we compute the distance between the endpoints of pairs of road arms, and subsequently select the endpoints sharing the shortest distance.

4.3 Road junction reconstruction

4.3.1 Ziplock snake

Traditional snakes (Kass et al., 1987), or parametric active contours are polygonal curves with which is associated an objective function that combines an image term, external energy, measuring the edge strength and a regularization term, internal energy, minimizing the tension and curvature. The curve is deformed so as to optimize the objective function and, as a result, to extract the image edges. Traditional snakes are sensitive to noise and need a close initialization. Since the junction border is composed of open curves with various degrees of curvature, close initialization often cannot be provided. As a result, traditional snakes get stuck in an undesirable local minimum. To overcome these limitations, the Ziplock snake model was proposed (Neuenschwander et al., 1997). Ziplock snakes are now briefly described here to provide a basis to introduce our approach. A Ziplock snake consists of two parts: an active part and a passive part (Fig. 6). The two parts are separated by moving force boundaries, and the active part is further divided into two segments, indicated as head and tail respectively. The initial positions of the head and tail segments are specified by an operator or a preprocessing module. Unlike the procedure for a traditional snake, the external force derived from the image is turned on only for the active parts. Thus the movement of passive vertices is not affected by any image forces. Starting from two short pieces, the active part is iteratively optimized to image features, and the force boundaries are progressively moved toward the center of the snake. Each time that the force boundaries are moved, the passive part is re-interpolated using the position and direction of the end vertices of the two active segments. Optimization is stopped when force boundaries meet each other. We call the external force used in the Ziplock snake traditional force field.

Ziplock snakes need far less initialization effort and are less affected by the shrinking effect from the internal energy term. Furthermore, the computation process is more robust because

the active part whose energy is minimized is always quite close to the contour being extracted. A Ziplock snake is an appropriate method to delineate the junction border if accurate initial points could be provided. We assume that these accurate fixed points can be obtained from the road extraction result.
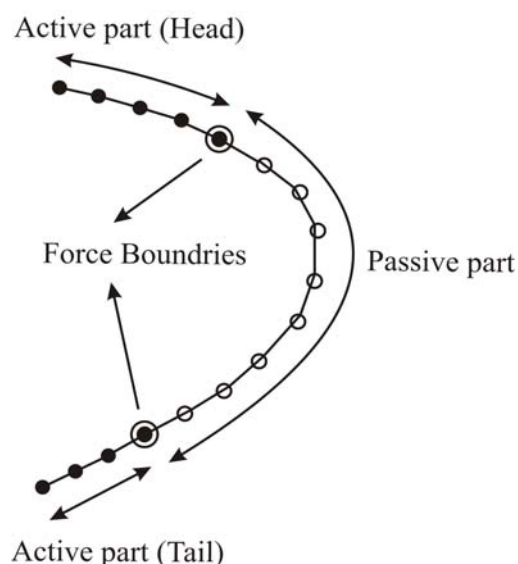

Figure 6. Illustration of a ziplock snake during optimization. A Ziplock snake, fixed at head and tail, consists of two parts, the active and the passive vertices. These areas are separated by moving force boundaries. The active parts of the snake consist of head and tail segments.

Nevertheless, Ziplock snakes are easily confused by disturbances caused by various features such as trees and their shadows, different kinds of road markings and the shadows from buildings, traffic lights, power lines and traffic signs. A strong internal energy can considerably decrease the effect of disturbing features. Furthermore, a global initialization is introduced to assure that snake vertices are distributed across the entire object boundary. The global initialization is provided by pairs of lines, each of which is defined by close endpoints and the intersection point of their related road sides (Fig. 7). These lines are divided up into equidistance vertices surrounding curve parts of the road junction.

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Figure 7. Illustration of the global initialization. Black lines are defined by two close endpoints and the intersection point of their respective road sides.

We tested the Ziplock snake method on several samples (Fig. 8-a, b). As opposed to low-resolution images where the road surface is quite homogeneous and road markings have less disturbing effects, in high-resolution images there are various disturbing features destabilizing Ziplock's active parts and subsequently hinder their motion. Furthermore, disturbing features, such as road markings as are shown in Fig. 8-a, besides destabilizing the active parts, i.e. no convergence occurs, pull the contour away from the desired boundaries. However, if the external force has a large capture range, it draws the contour back toward the object boundaries even from far distances. Since a traditional force field has a small capture range, Gradient Vector Flow (GVF) as an alternative external field was used.

a)   b)

Figure 8: Ziplock snake optimization using tradition force field as an external force. Black curves are the result of snake optimization. White lines are the extracted road arms. Since the capture range of the external force field is small, the iterations are stopped near the initial positions.

4.3.2 GVF Ziplock snake

The GVF field (Xu and Prince, 1997) was proposed to address two issues: a poor convergence to concave regions and problems associated with the initialisation. It is computed as a spatial diffusion of the gradient of an edge map derived from the image. This computation causes diffuse forces to exist far from the object, and crisp force vectors near the edges. The GVF field points toward the object boundary when very near to the boundary, but varies smoothly over homogeneous image regions, extending to the image border (Fig. 9). The main advantage of the GVF field is that it can capture a snake from a long range. Thus, the problem of far initialization is alleviated.

The GVF is defined to be the vector field $G(x,y) = (u(x,y), v(x,y))$ that minimizes the energy functional:

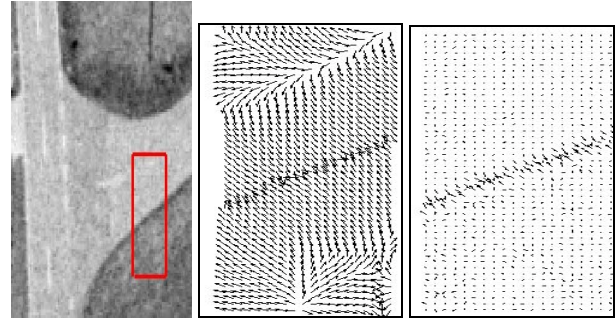a)   b)   c)

Figure 9: a) a small part of a test image
b) GVF field   c) Tradition force field

$$E = \iint \mu\left(u_x^2 + u_y^2 + v_x^2 + v_y^2\right) + |\nabla f|^2 |G - \nabla f|^2 dxdy$$

Where $f(x,y)$ is derived from the image having the property that it is larger near the image edges. μ is a regularization parameter which should be set according to the amount of noise present in the image. Using the *calculus of variations*, it can be shown that the GVF can be found by solving the following Euler equations:

$$\mu\nabla^2 u - (u - f_x)\left(f_x^2 + f_y^2\right) = 0$$

∇^2 is the Laplacian operator.

We call the Ziplock snake that uses the GVF field as its external force a GVF Ziplock snake.

Let $V(s) = (x(s), y(s))$ be a parametric active contour in which s is the curve length and x and y are the image coordinates of the 2D-curve. The internal snake energy is then defined as

$$E_{int}(V(s)) = \frac{1}{2}\left(\alpha(s)|V_s(s)|^2 + \beta(s)|V_{ss}(s)|^2\right)$$

Where V_s and V_{ss} are the first and second derivative of V in respect to s. The functions $\alpha(s)$ and $\beta(s)$ control the elasticity (the first term) and the rigidity (the second term) of the contour respectively.

The formulation for GVF Ziplock snake's motion can be written in the form (Kass et al., 1987):

$$V^{[t]} = (K + \gamma I)^{-1} * (\gamma V^{[t-1]} - \kappa P_v|_{V^{[t-1]}})$$

Where γ stands for the viscosity factor (step size) determining the rate of converges and t is the iteration index. κ alters the strength of the external force. The pentadiagonal matrix K contains the internal energy functions (α, β) and P_v is the GVF external force field.

4.3.3 Implemetation issues

In our implementation, we chose $\alpha = 0.001$ because the larger value forces the snake to become and then stay straight. Based on many tests on junctions of different shapes $\beta = 5$ was chosen to let the contour become smooth. To reduce the effect of disturbances, we set $\kappa = 0.1$, i.e. giving more weight to the internal force than to the external. Snake spacing refers to the distance between the sampled snake vertices. By experiment, denser snake vertices are more likely to be trapped and

destabilized by small disturbances (Fig. 10-a). Thus, convergence, assuming a small threshold to be achieved for the displacement from one iteration to the next, cannot be reached. Conversely, when snake vertices are too sparse, object boundaries with high change of curvature, as it is the case in road junctions, cannot be accurately delineated(Fig. 10-b). The snake spacing was confined within the range 7-10 pixels depending on how far two adjacent road arms are, so that their movement is less likely to be blocked by trees, single cars and road markings such as stop lines and cross walks.

a)   b)

Figure 10. In (a), snake spacing is 2 pixels, which signifies dense vertices, and the accuracy of convergence is 1/10 pixel. Active contours are caught in the shadow cast by the truck. In (b), snake spacing is 12 pixels and the accuracy of convergence is 1/200 pixel. The optimized active contour (black line) cannot delineate the junction border.

Likewise, the disturbing effect of the shadow cast by traffic lights and power lines are easily resolved. However, rows of cars standing behind the traffic light, and every large body of shadow from a row of buildings or trees might mislead the snake to converge to wrong boundaries, because in such cases, a large number of vertices are trapped in the disturbing object. This situation affects the motion of neighbouring vertices and eventually results in the delineation of the disturbing object boundaries or the leakage into either the road junction area or the surroundings. In our proposed approach, the force boundary is advanced one vertex per iteration when we can verify that the motion of the corresponding active part has stabilized. We evaluate each active part individually by testing if the displacement in x and y direction are less than a predefined threshold (1/200 pixel). Once two force boundaries collide, the viscosity factor is increased and the optimization is repeated simultaneously on all vertices since it improves the quality of the final result at places where there is a small deviation from the object boundaries. Intuitively, a little value of γ is chosen when the process starts, (because the curve is far from the solution) and a larger value when the snake is close to the contour (Berger and Mohr, 1990).

5. RESULTS

The contour-following property of Ziplock snakes, when combined with the large capture-range capability of the GVF force field, enables delineation of complex man-made objects in high-resolution aerial imagery. To demonstrate this potential, we tested the proposed approach on many road junction samples with the same set of parameters. Some of them are shown (Fig. 11). The problem illustrated in Fig. 8 is fixed. Furthermore, the approach can deal with disturbances caused by road markings and the shadow (bottom row image samples).

Figure 11. Top row image samples show rural areas and those in the bottom row are from suburb areas. In both groups, disturbances caused by road markings are resolved. Furthermore, the results in suburb areas are accurate even in the presence of shadows.

6. OUTLOOK

In this paper, we presented a new snake-based approach called GVF Ziplock snake to delineate the junction border resulting in the extraction of simple road junctions in the context of rural and suburb areas through the use of an existing geospatial database. We found that prior knowledge from an existing geospatial database can considerably facilitate the extraction. Furthermore, we demonstrated that our approach can overcome various kinds of disturbances. Further investigation into the possibility of using Balloon snakes in junctions whose central area lacks sufficient contrast with the surroundings causing the snake to be drawn outward of the junction area and to become straight rather than curvy, are warranted. Investigations into modelling islands' properties and extracting complex junctions and roundabouts are our next goals. Furthermore, optimal selection of the snake spacing constraint and the convergence threshold in images with different ground resolutions is desirable.

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