AUTOMATIC ROAD EXTRACTION BASED ON MULTI-SCALE MODELING, CONTEXT, AND SNAKES

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ABSTRACT

This paper approaches the problem of road extraction from three different directions. The first is the use of multiple scales. This combines detailed information of fine scale, like the markings, with abstract information of coarse scale, like the road network. The second direction is the extension of the multi-scale modeling with the context, i.e., the relations to other objects like buildings or trees. The context itself is split hierarchically into local context sketches, like *occlusion_shadow*, which is modeling a tree casting a shadow on the road, and global context regions, i.e., *open_rural*, *suburb_urban*, and *forest* areas which comprise the whole image. The context information is very useful to focus the extraction. The third direction taken in this paper is the use of snakes. So-called ribbon snakes are used not only to extract roads in a robust manner in fine scale, but they can be also used to bridge gaps in the extracted roads due to occlusions or shadows cast by buildings and trees. Practical examples show the validity of the approach.

1 INTRODUCTION

The most common methods for the extraction of roads are the detection or tracking of lines in coarse scale, i.e., low resolution imagery, and profile matching or detection of roadsides in fine scale, i.e., high resolution images. The approaches combine different methods and incorporate additional knowledge, e.g., geometrical constraints, in various ways. A main criterion to distinguish them is the interaction of a human operator. In semi-automatic schemes an operator selects an initial point and a direction for a road tracking algorithm (McKeown and Denlinger, 1988, Vosselman and de Knecht, 1995). In (Grün and Li, 1996, Merlet and Zerubia, 1996) the operator marks a few points of a road segment and an algorithm, e.g., based on dynamic programming, finds the road which connects these points (also in 3D for more than one image). This is advantageous because the path of the road is more constrained, and a more reliable handling of obstacles is possible. A similar approach based on so-called "ziplock" snakes is given in (Neuenschwander et al., 1995). These semi-automatic approaches can be extended to fully automatic operation by means of automatic seed point detection (Zlotnick and Carnine, 1993). A fully automatic approach is presented in (Barzohar and Cooper, 1996). Stochastic methods are used to find seeds for road extraction. Roads are found by dynamic programming based on a grey level model and on assumptions about the geometry of roads.

Road extraction is simpler if prior information is available. In an extreme case, the road given in a geographic information system (GIS) is verified only. This can be done by using steered anisotropic filters for the extraction of edges (Plietker, 1994) or by the analysis of profiles perpendicular to the road (Wiedemann and Mayer, 1996). One step further is taken in (de Gunst and Vosselman, 1997). Here the old GIS data is not only verified but anomalies in the verification are used to guide the search for new roads branching from the given roads.

If relations between roads and other objects, like cars, buildings, or trees, are neglected, a reliable extraction is often difficult. Background objects can have a strong influence on the characteristics of roads, or at least on the appearance of roads in aerial imagery. Consider for instance high objects like trees causing occlusions or casting shadows. In (Ruskoné, 1996), one of the most advanced approaches for road extraction so far is presented, which makes strong use of this contextual information to guide the extraction in complex scenes. The centers and direction of elongated regions found by a watershed-based segmentation on a gradient image are the seed points for the extraction of road segments by tracking the homogeneity of the road surface. By taking into account geometrical constraints, the road segments are connected, and the result is the road network. The road network is split up into short pieces which are classified into the so-called local contexts "road", "crossing", "shadow", "tree", and "field" according to several criteria concerning, e.g., the average grey value, or the straightness. The local contexts are validated in a second step. In urban areas, where profile matching or detection of roadsides would probably fail, this is for instance done by means of the detection and grouping of cars. (Ruskoné, 1996) is maybe the work closest to the one presented in this paper. (Bordes et al., 1997) analyze the influence of context on the ease of extraction of roads. Basically, three different kinds of contexts were distinguished: "rural", "forest" and "urban". Additionally, a distinction is made between different characteristics of the roads, like their type, and it is analyzed whether other linear objects like railways or rivers are running parallel to the road which might result in a misinterpretation. All this information is used to decide which segments should be verified first and, what is more, also which algorithm should be used for extraction.

This paper follows the work presented in (Baumgartner et al., 1997b), which essentially uses context information and multiple scales, based on the experience that distinct characteristics of roads can be detected best at different scales and in different contexts. Basically, multiple scales are used to model detailed information of fine scale, like the markings, as well as abstract information of coarse scale, like the road network. When fusing multiple scales, on the one hand, the abstract information is used to focus the extraction of the details. This avoids getting lost in the plethora of features in an image. On the other hand, details like markings can give very reliable evidence for a road.

The multi-scale modeling is complemented by context information which is divided into local context sketches, like *occlusion_shadow*, which is modeling a tree casting a shadow on the road, and global context regions, i.e., *open_rural*, *suburb_urban*, and *forest* areas, which comprise the whole image. The context sketches are related to the context regions: The context sketch *occlusion_shadow* for instance belongs to the context region *suburb_urban*. By this means the complex model for the object *road* is split into more specific sub-models which are adapted to the contextual environment. The sub-models emphasize certain characteristics of the objects and therefore can be regarded as specialized models. An advantage of context regions is that they can be used to focus the extraction: Road extraction in *open_rural* areas is easier and much more robust than in *suburb_urban* or in the *forest*. Thus, from the scale-space behavior and the context of the road a strategy for the extraction of the road can be deduced.

Up to now, snakes were mainly used for semi-automatic extraction. In the scope of the work presented in this paper they were found to show many advantages compared to the grouping scheme used in previous work for automatic road extraction (Baumgartner et al., 1997b). More specifically, the results of the coarse scale line extraction were used as the approximate centers for so-called ribbon-snakes used to extract the road in fine scale. Especially the ability to bridge gaps resulting from shadows cast on the road by trees or buildings (context sketch *occlusion_shadow*) is a new and very important feature of this approach. The main advantage of the snake for this application is that due to its geometrical stabilization, it can make use of the little information in the shadowed or short visible parts.

The paper proceeds as follows. In Section 2 the scale-space behavior of roads is analyzed, and a model for the extraction of roads is condensed from it. Section 3 defines the context sketches and assigns them different context regions. The model derived from scale-space behavior and the context of the road is complemented with a strategy for road extraction in Section 4. The snake-based approach is presented in Section 5. After giving some basics for snakes, the so-called ribbon snakes are introduced. After distinguishing *salient* and *non-salient roads*, results for road extraction are shown. The paper concludes with an outlook in Section 6.

2 SCALE-SPACE BEHAVIOR

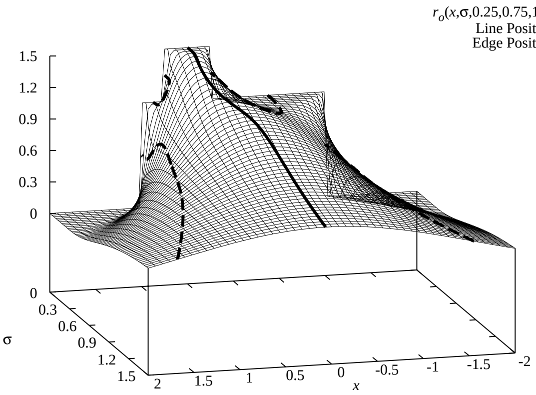
The appearance of roads in digital imagery depends on the sensor's spectral sensitivity and its resolution, i.e., inherent scale in object space. The remainder of this paper is restricted to grey-scale images, and only scale dependencies are considered. Images with various scale exhibit different characteristics of roads. In images with coarse scale, i.e., more than 2 m per pixel, roads mainly appear as lines establishing a more or less dense network. Opposed to this, in images with a finer scale, i.e., less than 0.50 m, roads are depicted as elongated homogeneous areas with more or less parallel borders and almost constant width.

In a smoothed image, i.e., a coarser scale, lines representing road axes can be extracted in a stable manner even in the presence of background objects like trees, buildings, or cars. Smoothing an image is hereby closely linked to the concept of "scale-space" for which (Lindeberg, 1994) gives a good introduction. Figure 1(a) displays a bar shaped bright line (= road) with a bright disturbance on the right side (= bright car on the right lane) and its behavior in scale-space for the line extraction model presented in (Steger, 1996). It is intuitively clear that only one line should be detected for all levels of smoothing, i.e., scales σ, and this is indeed the case. Figure 1(a) displays the line and edge positions mapped onto the smoothed profiles, while Figure 1(b) compares them to the corresponding positions of an undisturbed profile (ideal position). For small σ the extracted line position will be the one of the bright object, while for large σ it will correspond to the center axis of the line.

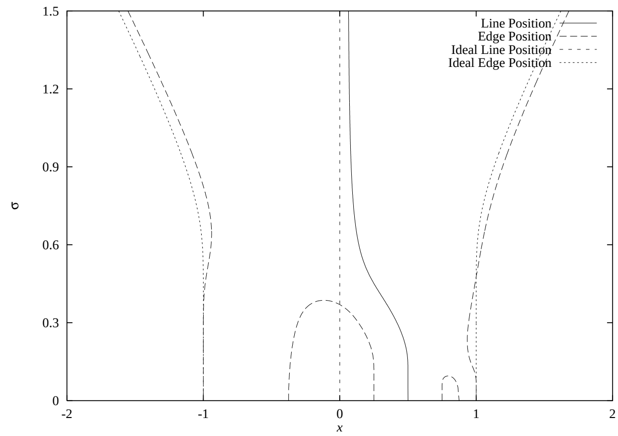
The outcome is that just by increasing the scale σ one can eliminate the car from the road. It can also be seen that the two edges corresponding to the bright object will vanish along with the flat inflection points on the undisturbed part of the line. As (Mayer and Steger, 1996) have shown, the appropriate scale for line extraction can be computed if the width of the line (=road) and of the disturbance (=car) as well as the contrast between background, line, and disturbance is given. Seen from a symbolical point of view, in the finer scale the substructure of the road (the car on the road or also objects like markings) has been eliminated. This can be interpreted as the *abstraction*, i.e., the increase of the level of simplification and emphasis of the road. Abstraction is achieved simply by changing the scale of the object.

From the last paragraph follows that fusion of coarse and fine scale results can contribute to improve the reliability of the road hypotheses. Additionally, details like road markings, which can be recognized at a resolution of less than 0.25 m, can be used as evidence to corroborate the detected road hypotheses. On the one hand, using multiple scales improves the robustness of road extraction. On the other hand, it results in the necessity to use different features at each scale, and to simultaneously combine all features of all scales into one road model. The semantic network in Figure 2 illustrates a simplified road model condensed from this (for a more complete model refer to (Baumgartner et al., 1997a)).

The model is split into three levels, defining different points of view. The *real world* level consists of the objects and their relations on a natural language level. In fine scale the road-segment is constructed of road-parts which in turn comprise the pavement and the markings. The objects in the *real world* level are connected to the objects in the *geometry and material* level by means of the *concrete* relation which connects *concepts* describing the same object on different levels, i.e., from different points of view. The *geometry and material* level is an intermediate level which



(a) Line and edge position in scale-space



(b) Extracted and ideal line and edge position

Figure 1: Scale-space behavior of a line with a bright disturbance on it.

represents the three-dimensional shapes of objects as well as their material (Tönjes, 1996). This level has the advantage that it represents objects independently from sensor characteristics and viewpoint, which is in contrast to the *image* level.

Road-segments in coarse scale are linked to a mostly straight bright line in the *image* level. In contrast to this, the pavement of the fine scale is linked to the elongated bright area in the *image* level via the elongated flat concrete of asphalt area in the *geometry and material* level. The markings are related to bright lines via colored lines. Whereas the fine scale gives detailed information, the coarse scale adds global information. If the information of both levels is fused, false hypotheses for roads are eliminated by using the abstract coarse scale information, while integrating details from the fine scale, like the correct width of the roads. With this, the advantages of both scales are merged.

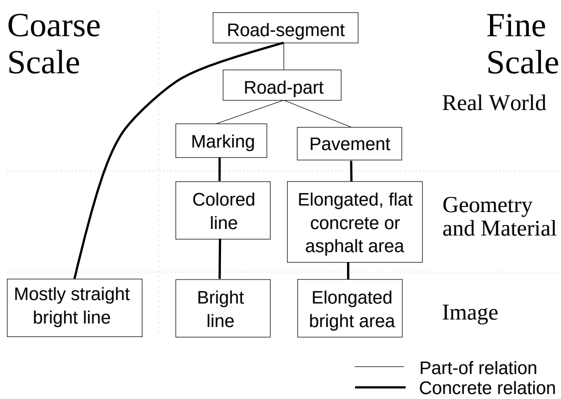


Figure 2: Road model: different scales and points of view

3 CONTEXT

Besides features which refer to the road itself, relations between roads and other so-called background objects, like buildings, trees, and cars, are very important for the recognition of objects. Background objects on the one hand support and on the other hand hinder road extraction.

The concept "context sketch" is introduced to describe typical relations between road objects and background objects. The context sketch *occlusion_shadow* consists of a hypothetical road-part which connects two road-segments and a high object next to the hypothetical road-part. Figure 3a) illustrates an occlusion, and Figure 3b) a shadow cast onto the road by a high object. The relation between roads and parallel objects, like sidewalks and cycle-tracks, is defined by the context sketch *parallel_object*. Another context sketch describes the relation between road-segments and driveways to agricultural fields (*rural_driveway*). There is a small number of other basic context sketches which should be enough to model most of the relations of roads to other objects.

Of major importance for the usefulness of context sketches is that they do not have to be taken always into account. This is in contrast to approaches representing the whole scene with one model (Matsuyama and Hwang, 1990). The relevance of features and relations depends also on the so-called global context. Roads in *suburb_urban* areas look quite different and have different relations than roads in *open_rural* or *forest* areas. Therefore, this paper proposes to use different features and relations, i.e., context sketches, not only at multiple scales but also within different context regions, for which *suburb_urban*, *forest*, and *open_rural* areas are distinguished here. Information from a GIS or a (pre-) segmentation of the image into these regions provides global a priori information about the characteristic features and their relations. For example, buildings in downtown areas are – in contrast to buildings in *open_rural* areas – very close and highly parallel to roads; sidewalks and cycle-tracks are more likely to appear in *suburb_urban* areas; in *open_rural* areas single trees and single buildings might hinder extraction, whereas in *forest* regions mainly shadows and occlusions pose problems. This information about existence or proximity of background objects makes it possible to choose the most appropriate extraction algorithm and to determine the meaning of distinct road-parts and road-segments. The assignment of the context sketches to context regions is shown in Figure 4.

In practice, the road is modeled with different semantic objects, like road-parts and road-segments, implemented as C++classes. The ability of the objects to explicitly represent a specific area also facilitates looking for additional evidence, e.g., road markings, which otherwise is very hard to find.

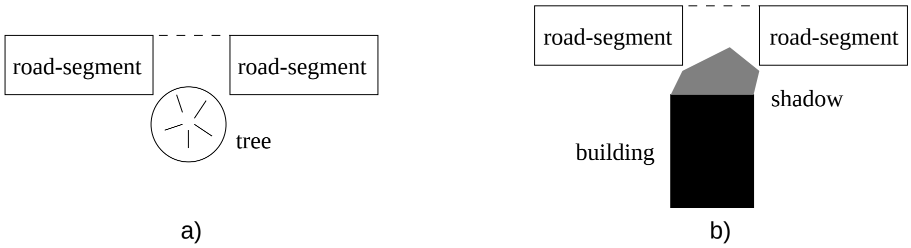


Figure 3: Context sketch *occlusion_shadow*

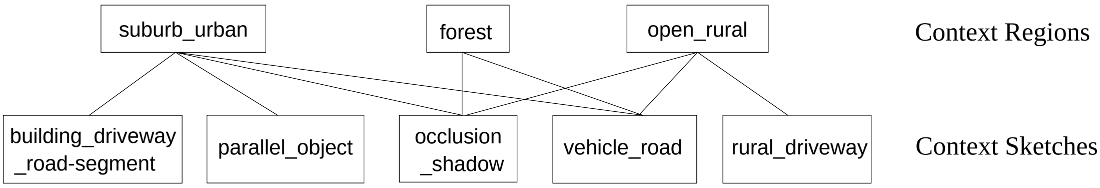


Figure 4: Context regions and context sketches for roads

4 STRATEGY

From the scale-space behavior of the roads and the model for their context the following strategy for their extraction can be deduced. It is based on the principle "hypothesize and test", and focuses on single objects ("local feature focus" (Grimson, 1990)) by postulating that the focus should consider:

- Object is easy to extract
- Object can be extracted with high confidence
- Object has a big importance for the overall extraction

The resulting strategy is (Baumgartner et al., 1997a):

1. Start extraction in *open_rural* area
2. Extract hypotheses for roads in coarse scale
3. Extract roads in fine scale; verify by means of markings or cars
4. Expansion of the road-network by a complex interaction of
   (a) Closing gaps based on local context
   (b) Propagation of the network in other global contexts

For the expansion of the network in 4. (Steger et al., 1997) show an approach which uses the information of the whole network to find out which parts should be connected.

In the next Section a snake-based approach is presented which not only gives good results for the extraction of roads but also gives a means to bridge the gaps caused by small occlusions or by shadows cast on the roads.

5 SNAKES

This Section is based on results from (Laptev, 1997), where details of the approach can be found.

5.1 Basics of Snakes

The concept "snake", also called "active contour model" was originally introduced in (Kass et al., 1987). It combines internal smoothness constraints like bending of a curve with image forces like the gradient. This idea can be represented as a sum of its energies

$$E(\vec{v}) = E_{img}(\vec{v}) + E_{int}(\vec{v}) + E_{ext}(\vec{v}), \quad (1)$$

where E_{int} represents the *internal energy*, E_{img} the *image energy* and E_{ext} the *external forces*. The position of the snake where all these forces compensate each other corresponds to the local minimum of the snake's total energy E. Thus, the problem of the optimization of the snake's position is equivalent to the minimization of its energy.

The image energy of the snake can be defined as:

$$E_{img}(\vec{v}) = -\int_0^1 P(\vec{v}(s,t))ds, \quad (2)$$

where $P(\vec{v}(s,t))$ is a function with high values corresponding to the features of interest. When attracting the snake to edges in images, $P(\vec{v}(s,t))$ is usually taken equal to the magnitude of the image gradient, that is

$$P(\vec{v}(s,t)) = |\nabla I(\vec{v}(s,t))|, \quad (3)$$

where $I(\vec{v}(s,t))$ is the raw image or – more often – the image convolved with the Gaussian kernel. The convolution with Gaussian kernel smoothes the image and removes disturbances which prevent the snake from moving toward the positions with lower image energy corresponding to the more salient image features.

The internal energy makes it possible to introduce geometric constraints on the shape of the snake. It can be defined as

$$E_{int}(\vec{v}) = \frac{1}{2}\int_0^1 \alpha(s)\left|\frac{\partial\vec{v}(s,t)}{\partial s}\right|^2 + \beta(s)\left|\frac{\partial^2\vec{v}(s,t)}{\partial s^2}\right|^2 ds, \quad (4)$$

where $\alpha(s)$ and $\beta(s)$ are arbitrary functions that control the snake's tension and rigidity. The constraint on tension is introduced by the first order term and makes the snake act like a membrane. The rigidity is constrained by the second order term and makes the snake act like a thin plate.

In order to find the optimal position for the snake, its energy has to be minimized. According to the variational calculus this must be a solution to the *Euler-Lagrange* differential equation of motion. When choosing a particular deformation energy the differential equation controling the motion of the snake becomes linear and can be separated. This has the advantage of solving one optimization step in linear time. For the actual implementation the equations have to be discretized. For details of this refer to (Laptev, 1997).

5.2 Ribbon Snakes

The goal of this paper is to extract roads, i.e., linear features with significant width. They can be modeled by ribbons whose sides correspond to the features' boundaries. Using ribbon snakes, linear features can be extracted by optimizing the position and the width of the ribbon. In order to represent ribbon snakes, the parametric curve $\vec{v}(s,t)$ can be augmented by the third component $w(s,t)$ (Fua and Leclerc, 1990):

$$\vec{v}(s,t) = (x(s,t), y(s,t), w(s,t)), \qquad (0 \le s \le 1), \tag{5}$$

Such representation implies that each slice of the ribbon snake $\vec{v}(s_0,t_0)$ is characterized by its width $2w(s_0,t_0)$ and the location of its center $(x(s_0,t_0), y(s_0,t_0))$. All center points compose the centerline of the ribbon (cf. Figure 5 (a)).

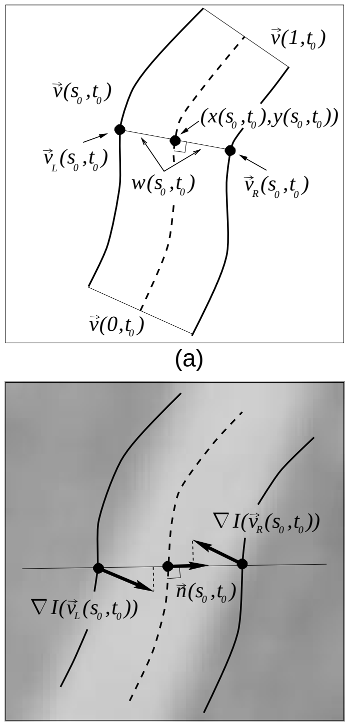
In order to perform the optimization of the ribbon snake, the forces which act on it have to be defined. The advantage of the ribbon's representation in equation (5) is that the expression for the snake's internal energy E_{int} can be directly used for ribbon snakes. Doing so, the width of ribbons will be constrained by tension and rigidity in the same way as the two coordinate components. The internal forces which act on the ribbon snake will on the one hand constrain ribbon's centerline to be a smooth curve. On the other hand, they will control the distance between the ribbon's sides, forcing the sides to be parallel.

In contrast to the original snakes, the image information for ribbon snakes has to be taken into account not at the center of the curve $(x(s,t), y(s,t))$, but at the ribbon's left and right sides. As shown in Figure 5 (a), for each slice of the ribbon $\vec{v}(s_0,t_0)$ there exist two points $\vec{v}_L(s_0,t_0)$ and $\vec{v}_R(s_0,t_0)$ corresponding to the ribbon's left and right sides. The position of these points composing the ribbon's boundaries $\vec{v}_L(s,t)$ and $\vec{v}_R(s,t)$ can be expressed as

$$\begin{aligned} \vec{v}_R(s,t) &= w(s,t)\vec{n}(s,t) \\ \vec{v}_L(s,t) &= -w(s,t)\vec{n}(s,t), \end{aligned} \tag{6}$$

where $\vec{n}(s,t)$ is the unit *normal* vector of the ribbon's centerline (cf. Figure 5 (b)). Adapting the expression for image energy E_{img} in equation (2) to ribbon snakes, the function $P(\vec{v}(s,t))$ in equation (3) has to be redefined. Requiring the image contrast to be large along the left and the right side of the ribbon, P can be defined as the sum of the image gradient magnitudes on the left and right ribbon sides:

$$P(\vec{v}(s,t)) = |\nabla I(\vec{v}_R(s,t))| + |\nabla I(\vec{v}_L(s,t))| \tag{7}$$



(b)

Figure 5: (a) Parametric representation of the ribbon snake. Each slice $\vec{v}(s_0,t_0)$ is identified by center $(x(s_0,t_0), y(s_0,t_0))$ and width $2w(s_0,t_0)$. (b) Image gradients for the two sides of the ribbon and their projection onto the ribbon's unit normal vector $\vec{n}(s_0,t_0)$.

However, when searching for linear features which are known to be brighter or darker than their surroundings, the result of the extraction can be improved if the direction of image gradients at the left and right sides of the ribbon will be taken into consideration, too. For example, the extraction of bright linear features implies that the image intensity at the ribbon sides has to change from dark to bright at the left ribbon side and from bright to dark at its right side (cf. Figure 5 (b)). This is equivalent to demanding the projection of image gradient on the vector $\vec{n}(s,t)$ to be negative along the ribbon's left side $\vec{v}_L(s,t)$ and positive along its right side $\vec{v}_R(s,t)$. Taking this into account, the function $P(\vec{v}(s,t))$ can be redefined as

$$P(\vec{v}(s,t)) = (\nabla I(\vec{v}_L(s,t)) - \nabla I(\vec{v}_R(s,t))) \cdot \vec{n}(s,t). \tag{8}$$

5.3 Salient and Non-Salient Roads

Up to this point, only a means to extract the road in the fine scale (i.e., point number 3. in Section 4), when a good approximation of the road is already there, was presented. To automatically extract roads the prerequisite is an approximation of the road. However, as given by point number 2. in Section 4, this can be gained from line extraction in coarse scale (Steger, 1996). Figure 6 (a) presents the result of line extraction and Figure 6 (b) the result of optimization of the ribbon snake. The center of the ribbon snake was initialized with the center of the line and the width was set to 0. Then the ribbon snake was optimized with an external force pushing the sides outwards. Whereas Figure 6 (b) is considered to have a good constancy of the width and is therefore accepted as a so-called *salient road*, Figure 6 (c) shows a great variation of the width and is therefore not

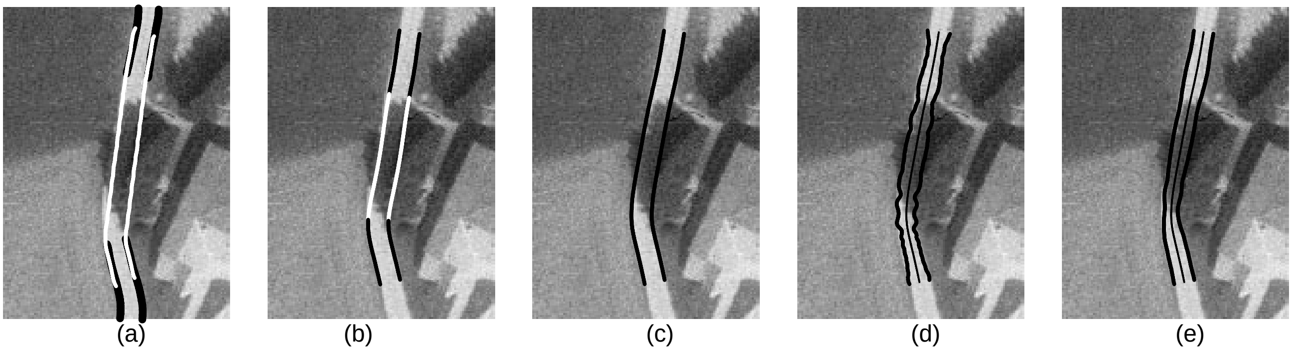


Figure 7: Optimization of ribbon snakes at a **correctly hypothesized** *non-salient* road. (a)-(c) Optimization of ziplock ribbon with constant width and fixed end points. White lines indicate passive part. (d)+(e) Optimization of the ribbon's width with fixed centerline

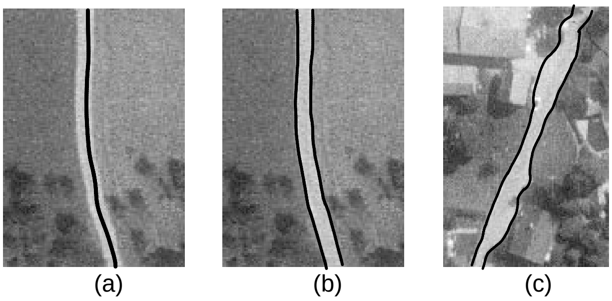


Figure 6: Optimization of ribbon snakes initialized at the centerlines of hypothesized roads. (a) centerlines (b) constant width $\Rightarrow$ *salient road* (c) no constant width $\Rightarrow$ *non-salient road* or no road at all

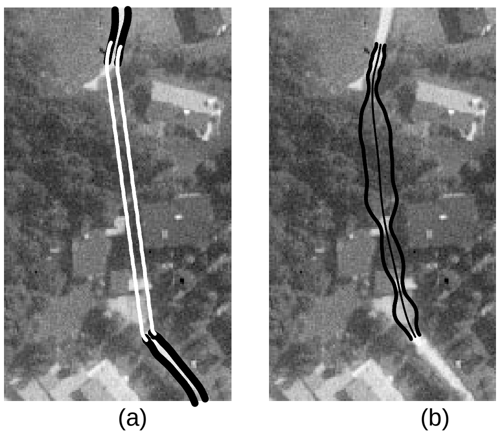


Figure 8: Optimization of ribbon snakes at a **wrongly hypothesized** *non-salient* road. (a) Optimization of the ziplock ribbon between given ends of *salient* roads. (b) The result of the expansion of the ribbon's width.

accepted as a road.

When all *salient roads* have been extracted, in most cases smaller or larger parts of the road-network are still missing. To find further parts of the network so-called *non-salient* roads are introduced. They are extracted as follows: The starting points are always two ends of *salient roads* for which a connection is hypothesized (cf. point number 4.(a) in Section 4). The hypotheses can be generated by the sophisticated algorithm of (Steger et al., 1997), but in many cases a connection of nearby ends of *salient roads* works as well. The two ends are connected by a ribbon snake and are optimized using the ziplock principle (Neuenschwander et al., 1995). This idea prevents that in case the two endpoints of a snake are known and one optimizes the whole snake at once the snake is stuck to disturbances in between. This is done by optimizing at first only the parts close to the ends and then propagating this information from both sides until the whole snake is optimized. For locating *non-salient roads* this helps but is not enough, and another strategy was found to be of major importance (Laptev, 1997): with the ziplock snake only the center of the road is optimized. The width is taken to be constant and equal to the average of the width of the two *salient roads*. Then in a second step the centers are fixed and only the width is optimized. *Non-salient roads* can again be distinguished from other objects by the constancy of the width (cf. Figures 7 and 8). Whereas in Figure 7 the width is relatively constant, and therefore the hypotheses of a *non-salient road* is accepted, in Figure 8 it is not.

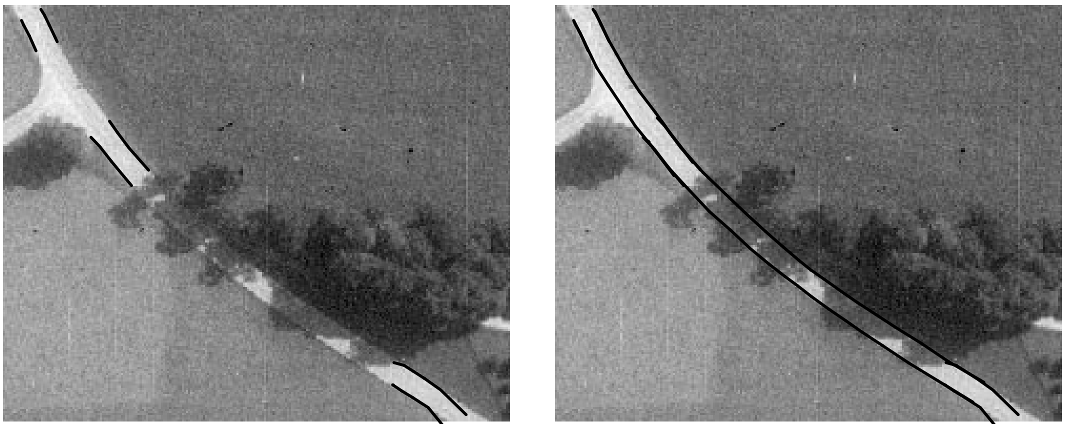
In Figure 9 the result for a larger image combining the extraction of *salient* and *non-salient roads* is given. The approach is able to bridge not only short gaps caused by single trees casting shadows on the road (cf. left part of the image) but also longer gaps like the one close to the building in the lower left part of the image. This shows that it is possible to bridge the gaps modeled by the context sketch *occlusion_shadow*. An even better example for this is presented in Figure 10, where a long shadowed part is bridged by a *non-salient* road.

6 CONCLUSIONS

This paper has shown three basic components which are useful for the extraction of roads from aerial imagery: Modeling of scale-behavior and of context as well as the extraction in fine scale by means of ribbon snakes. Results for the combination of scale-behavior with the snakes have shown quite satisfactory results.

Nevertheless there still is much to be done. Right now development is on its way to also integrate the context information. This is of big importance as only a serious analysis of the causes of gaps can be the basis for a reliable bridging. As occlusions and shadows are caused by the three-dimensional extent of objects, this has to be integrated. Results in (Eckstein and Steger, 1996) show that it is possible to predict shadows and to segment them in the image based on results from surface reconstruction. Similarly, occlusions can be predicted.

Figure 9: *Salient* and *non-salient roads* for a larger image



(a) (b)

Figure 10: (a) *Salient* and (b) *non-salient roads* for a shadowed part

To make the extraction of roads more reliable and make it work in different contexts, the fusion of different information or techniques is necessary. A deficiency of the approach presented here is for instance the recognition of cars (Ruskoné et al., 1996). Also the handling of more complicated crossings is an issue which still has to be solved.

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