ADAPTATION OF OBJECT MODELS FOR ROAD EXTRACTION IN IMAGES OF DIFFERENT RESOLUTION

J. Heller and K. Pakzad

Institute of Photogrammetry and GeoInformation, University of Hannover
Nienburger Str. 1, 30167 Hannover, Germany – (heller, pakzad)@ipi.uni-hannover.de

KEY WORDS: Interpretation, Model, Scale, Knowledge Base, Multiresolution, Representation, Generalization

ABSTRACT:

Depending on the spatial resolution, the appearance of roads differs in images. In high resolution aerial images a road might be distinguishable as an area with visible road markings, while in a satellite image of low resolution, roads appear as lines and their network character becomes important. The design of the object model for the extraction of roads therefore has to be influenced by the resolution of the available imagery.

In this paper we present results of a concept to automatically adapt road models for high resolution images to models suitable for any other lower resolution images with the same spectral characteristics. The road model is formulated as a semantic net, which ensures an explicit representation of objects. Starting from the manually created semantic net for high resolution images and the given target scale, the road model is first automatically decomposed into object parts with similar scale behaviour. The representation of the object parts in the coarser scale is then automatically predicted by scale change models, which are generated by deploying analytical as well as simulation procedures. After scale adaptation of the decomposed object parts, they are fused back to a complete object model in form of a semantic net, which is suitable for road extraction in images of the lower target resolution.

The automatically created semantic nets for different scales are used for automatic object extraction. Using an object model for road extraction in urban areas, the developed methods were successfully tested. The presented methodology facilitates the creation of new object models for automatic object extraction in lower resolution images by adaptation, and therefore avoids redundant work.

1. INTRODUCTION

Landscape objects appear differently in images of varying spatial resolution. Depending on its size, an object might be perceptible as an area or barely visible as a point in an image of a certain spatial resolution. The same applies for the reduction of the resolution to an object of the same size – with increasing pixel size of the image the object will appear simplified with less detail until it disappears. A prerequisite for the reliable extraction of landscape objects is the development of suitable object models. However, due to the varying appearance of the same object in different resolution the model for the object extraction must be modified to fit to each spatial resolution. Thus, various object models have to be created for the same object. All information needed for the description of the object in low resolution is already contained in the object models for high resolution, as in the process of scale reduction no new details appear. Hence, redundant work for the creation of low resolution object models can be avoided, if there already exists an object model for high resolution images.

In this paper an approach to derive automatically object models for low resolution images from models created for high resolution images is presented. The object model for high resolution is to be formulated manually as a semantic net, which ensures an explicit representation of objects. The focus for objects to be investigated lies on line-type features, such as roads and railways. The developed methodologies are presented here and tested exemplarily on an object model describing a dual carriage highway. As roads are dominant landscape features, they are subject to ongoing research in the field of image analysis. Object models were developed for various road types, contexts and spatial resolutions [Wiedemann02, Baumgartner03, Hinz04]. Extensive research has also been carried out on the fundamentals of linear scale-space theory [Witkin86, Lindeberg94, Florack94] and its application, e.g. on feature detection [Lindeberg98]. Investigated was also the scale behaviour of line-type features [Steger98, Mayer98]. By combining scale-space theory with object modelling in [Baumgartner03, Hinz04], object models integrating different image resolution levels in a single model were proposed. In [Mayer&Steger98] scale events in linear scale-space for roads and for buildings in morphological scale-space [Mayer00] were analyzed and predicted. But, so far, the analysis of complete object models in scale-space and the adaptation to another scale is missing. The general strategy for the adaptation of semantic nets to a coarser scale was presented in [Pakzad&Heller04] incorporating first examinations concerning the scale behaviour of feature extraction operators and demonstrating the strategy using an example in an adaptation process carried out manually. Necessary constraints for the creation of the initial object models in order to ensure the models' automatic adaptability were also stated.

In section 2 a repetition concerning the general strategy of the procedure is given and the different steps are briefly described. The relevant concepts of linear scale-space theory are briefly summarized in section 3. The characteristics of line-type objects in scale-space and the thereof derived methodologies used in the automatic adaptation algorithm are explained in section 4. Section 5 contains an example for an adaptation of a particular road model to coarser scales. The last section gives a summary and draws conclusions from the presented paper also for future work.

2. STRATEGY FOR SCALE ADAPTATION

The general strategy for the automatic adaptation of object models can be divided into three main steps that enable the separate scale-space analysis of object parts for the prediction of their scale behaviour while scale changes (cf. Fig.1).

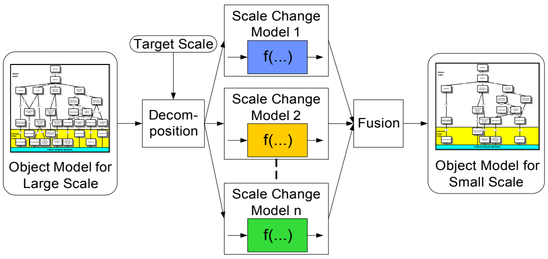


Figure 1. Strategy for Scale Adaptation

With knowledge of the target scale, the original object model for high spatial resolution is at first decomposed into object parts with similar scale change behaviour as well as in neighbouring objects parts that interfere each other's appearance in the coarser scale.

These groups of object parts are then analyzed separately regarding their scale behaviour. Their appearance in the lower target resolution is predicted by scale change models. At last, all predicted objects are composed back to a complete object model, suitable for the extraction of that object in images of the lower target resolution.

3. LINEAR SCALE-SPACE

The reduction of spatial resolution is a matter of scale change. Due to the direct relationship between scale and spatial resolution in aerial images, the analysis may be undertaken in scale space to examine a change in resolution. The scale space analysis regarding the object parts of the semantic net is carried out deploying the concepts of linear scale space theory, first introduced by [Witkin86]. A family of signals serves as multi-scale representation which can be generated from the original signal dependent on only the scale parameter $\sigma \in \mathrm{R}_+$. With only this single parameter any other level of scale can be described, while the original signal corresponds to σ=0. For the creation of another scale level, the original signal is convolved with the Gaussian kernel generated with the respective scale parameter σ:

$$g(x,\sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} \qquad (1)$$

The signal family derived from the Gaussian kernel fulfils the diffusion equation and has some unique characteristics: It is isotropic and homogeneous, i.e. no direction or location is preferred during scale change.

Objects may interfere with each other as scale becomes coarser. According to [Lindeberg94] there are 4 events in scale space to be distinguished:

- Annihilation : an object disappears
- Merging : several objects merge into a single object
- Creation : a new object is created
- Split : a single object splits into two or more objects

Creation and Split events are extremely rare and not relevant to parallel line-type objects. However, possible scale events of Annihilation and Merging may take place while scale changes from the original to the coarser target scale and therefore need to be considered in the scale change models, as these events influence the remaining objects.

The line-type objects (lines and stripes) subject to the analysis are exclusively elongated and parallel. The examination of the lines' profiles is therefore sufficient and reduces the problem to one dimension. The object type "Stripe" can be regarded as a broad line and its behaviour in scale-space is comparable to that of lines. Therefore, in the remaining of this paper it will solely be referred to lines.

4. METHODOLOGY

In the hereby presented adaptation methods, only line-type objects, i.e. lines and stripes, are considered.

4.1 Decomposition of the Object Model

All object parts are separated regarding their object type and interference with each other as scale changes to the target scale. For the lines appearing in road models, as a realistic profile a bar-shaped line with width w and contrast c is assumed, given by the following definition:

$$f_b(x) = \begin{cases} c, & |x| \le w \\ 0, & |x| > w \end{cases} \qquad (2)$$

In the discrete space (as we have with digital images) the likely existence of interaction in the target scale between two adjacent objects can be determined by their distance and the width of the filter that is used for the generation of the image in coarser scale. As long as the filter width is smaller than the distance of the objects, no interaction will take place. When the filter width becomes larger than the object distance, the objects might influence each other's appearance and therefore need to be grouped to be analyzed together regarding their scale behaviour. Hence, the case of interaction can easily be handled by a comparison of the filter width w_f and the object distance $d_{1/2}$. The geometric relation is depicted in Fig.2.

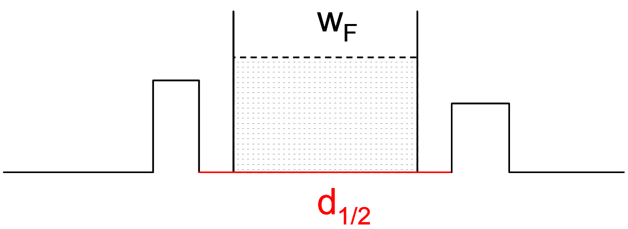


Figure 2. Dependency of Interaction between two Objects from the Filter Width and Object Distance

Based on these relations, all object parts of the original object model are sorted into single lines or groups of lines in the decomposition process (cf. Fig. 3). A decomposition module undertakes this task.

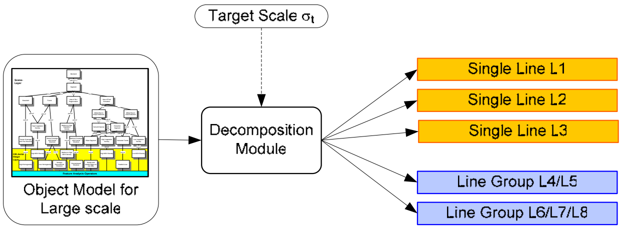


Figure 3. Decomposition of the Initial Object Model

4.2 Scale Change Models

For all object parts that were separated in the decomposition step, their appearance in the target scale is to be predicted by the scale change models. This task can principally be coped with in an analytical or empirical way. The scale change models we propose use a combination of these two possible solutions due to practical reasons.

The decomposed object parts are at first investigated for possible scale events of Merging and Annihilation, as they affect the type and number of the resulting objects in the small target scale.

Merging

In the case of a group of lines, the adjacent lines will at a certain scale start interacting with each other depending on their distance apart, as described above. For a larger scale parameter σ there will be two distinct maxima enclosing a single minimum in the profile of the lines (cf. Fig.4). With even larger σ the minimum will eventually disappear and there will remain only one single maximum, signalling the Merging of the adjacent lines. The evolution of Merging levels over scale space can be divided into three zones. In the first zone the objects are clearly distinctive and apart from each other. Between the point, where interaction between the objects starts, and the point of definite Merging with only a single maximum in the profile left, lies the "Domain of Uncertainty", in which the adjacent lines have started influencing each other's appearance, but did not merge completely yet. In the third and last zone, the Merging of both objects has entirely finished and the merged objects will behave from there on in scale space like a single object. The corresponding zones with their different Merging levels are also depicted in Fig.4 with an example for a line group profile and image for each zone. Although Fig. 4 shows exemplarily two adjacent lines with the same width and the same intensity, the algorithm developed for the scale change models is able to handle arbitrary width and contrast of the analyzed objects.

The extraction of objects of the semantic net in images is done by feature extraction operators bounded to the nodes of the object parts. The characteristics of the operator determine the separability of objects and therefore the number of objects in the lower scale net. In the first zone before interaction takes place, the operator will surely detect two separate lines, while in the last zone, after the definite Merging, any operator can only extract one single line. In the "Domain of Uncertainty", the number of objects that are extracted is uncertain, but is dependent on the characteristics of the feature extraction operator. The operator will have its own usability threshold in scale space for the case of Merging. This threshold can be found best by empirical analysis. The feature extraction operator, which is bounded to the semantic net in order to extract the object of the particular object type, is applied to a synthetic image simulating the line group with its attributes. Otherwise, the number of the resulting objects in lower scale will stay uncertain. Due to the empirical analysis, the algorithm is very flexible, since it remains independent from the user's choice of the operator and also practicable, as there are quite a few different line extraction operators existent and an analytical modelling of the scale behaviour of all relevant operators would exceed the realizable amount of work.

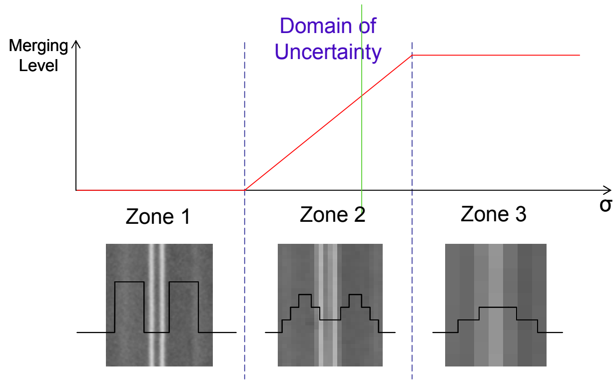


Figure 4. Merging Zones and Usability Threshold of the Feature Extraction Operator

To determine whether the target scale falls into the "Domain of Uncertainty" the line profile in the target scale is tested using means of differential geometry. By calculating the point of interaction and testing for definite Merging by the searching for the existence of a minimum, the zone, in which the target scale is located, can be found. The result of the operator applied to a synthetic image simulating the line group with their attributes in the target scale will express the operators' ability to extract the lines of this particular group separately and therefore determine the number of objects in the resulting semantic net in the target scale.

For the case of interaction, a shift in line position of the resulting object could occur, if the Merging level is advanced enough. For the determination of the modified line position the result of the feature extraction operator that is applied to the synthetic image simulating the target scale is used.

Annihilation

According to [Steger98] the responses of the convolution of the bar-shaped line profile (notations as in section 4.1) with the Gaussian function g(x,σ) can be calculated by:

$$r_b(x,\sigma,w,c) = f_b(x) * g(x,\sigma) \qquad (3)$$

$$= \mathrm{c}(\Phi_\sigma(\mathrm{x}+\mathrm{w}) - \Phi_\sigma(\mathrm{x}-\mathrm{w})) \qquad (4)$$

where

$$\Phi_\sigma(x) = \int_{-\infty}^{x} e^{-\frac{t^2}{2\sigma^2}} dt \qquad (5)$$

In continuous space a single line will become wider and flatter when convolved with the Gaussian function, but the centre of the line will not disappear entirely as long as the scale parameter σ is smaller than infinity.

In discrete space, however, by convolving the line profile with increasingly large Gaussian kernels the line will become flatter and wider until the line disappears at a certain size of the Gaussian kernel. Annihilations in discrete space can be calculated numerically by the convolution integral of the function describing the bar shaped line profile and the Gaussian function with the corresponding scale parameter of the target scale σ_t . The value of the convolution integral determines the grey value displayed in a discrete pixel matrix of the resulting image. As long as the response value stays larger than the smallest quantisation step of the displayed image, the object will still exist. Only when the grey value falls below that threshold, the object has disappeared. Thus, Annihilation has certainly occurred during scale reduction, if the following statement is true:

$$r(x=0,\sigma_t,w,c) < r_Q \qquad (6)$$

where r_Q : smallest quantisation step (grey value of 1)

In this case, no feature extraction operator will be able to extract a line. But an operator can possibly fail to extract a line as well for small grey values depending on its parameter, mainly on the set thresholds. In this range of contrast the occurrence of Annihilation depends on the operator. We use for the upper limit of this range a grey value of 15 as a realistic value from which a reliable feature extraction operator should be able to detect a line. However, this upper limit can be set according to the individual character of the operators extracting the objects. Here again, the operator is applied to a simulating synthetic image and the result of the operator is used to determine the scale event, if the calculated response of the convolution integral is below the upper range limit.

Attributes

The attributes for the nodes in the semantic net of the target scale can also be found analytically. The attribute "Grey Value" is given by the grey value of the hierarchically higher node (in our example the pavement) plus the contrast of the line centre, which can be calculated by solving the convolution integrals for the object in the target scale.

The attribute "Extent" is expressed by the width of the line, which is the distance of the edges delineating the line. The edges could be found by the inflection point of the line profile in the target scale, which can be determined using differential geometry. The gradient in the direction perpendicular to the line has its largest absolute value at the site of the edge. However, the scale space analysis for this problem cannot be solved straight forward [Steger98a]. Therefore, the edge positions are in the adaptation algorithm determined by using the gradient image with the corresponding target scale smoothing factor σ_t of the simulated line or line group with its attributes.

The value of the attribute "Periodicity" can only change for periodic lines (p<1). The periodicity can alter, if the gap between the line parts is subject to interaction, which can be determined by a similar comparison of filter width and gap length as already used in the decomposition module. In the case of interaction, the change of gap length between the line parts is determined by a similar procedure like the line width from the gradient image. From this value, the proportion of the line length and the gap, i.e. the periodicity of the line, can be derived.

4.3 Fusion of the Object Model

At last, all the object parts, whose appearance in the target scale was predicted, have to be fused back to a complete semantic net describing the object in the target scale (cf. Fig.5) considering the scale events and new attributes. In the case of Annihilation, the affected nodes do not reappear in the target scale net, and all relations to other nodes will be dissolved. For a Merging event the remaining number of objects is also reduced.

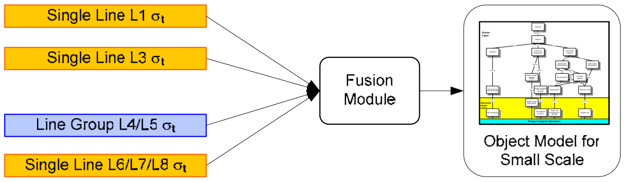


Figure 5. Fusion of the Object Model for Target Scale

The hierarchical and spatial relations of the other nodes do not change to the original net. Only the distances of the objects $d_{\delta Li,Lj}$ in the target scale need to be adapted, if the object's width has changed and the line position has shifted due to Merging:

$$d_{\sigma_t L1,L2} = d_{L1,L1} - \tfrac{1}{2}\Delta w_{\sigma_t L1} - \tfrac{1}{2}\Delta w_{\sigma_t L2} + t_1 + t_2 \qquad (7)$$

where

$d_{\sigma_t Li,Lj}$: distance of line i and line j in target scale

$d_{Li,Lj}$: distance of line i and line j in initial scale

$\Delta w_{\sigma_t Li}$: change of width of line i

t_i : translation of position of line i

5. EXAMPLE FOR SCALE ADAPTATION

In this section, results of the automatic adaptation process described in section 4 for an exemplarily created object model for roads are presented. The methodology is applied to the slightly simplified object model for a dual carriageway introduced in [Pakzad&Heller04] suitable for images of high resolution (3.3-7cm), fulfilling the developed constraints for the creation of automatically adaptable semantic nets. The simplification is done due to representation reasons. The road model used in this example is depicted in Fig.6.

To demonstrate the capability of the developed methodology, the automatic adaptation is carried out for 2 target scales. As target scales σ_{t1}=25 and σ_{t2}=100, corresponding to a spatial resolution of about 2.6m and 10.4m respectively, were chosen exemplarily, because they represent middle to strong scale change. The methods were implemented using the image processing system HALCON 7.0.

A synthetic image simulating the object parts with its attributes and spatial relations in the original scale was created for the empirical analysis of the scale events and determination of the attributes (Fig.7). The image simulating the lines was created using the attributes from the nodes of the original semantic net. The contrast of the lines was deduced from the difference of the grey values of the road markings and the hierarchically higher pavement.

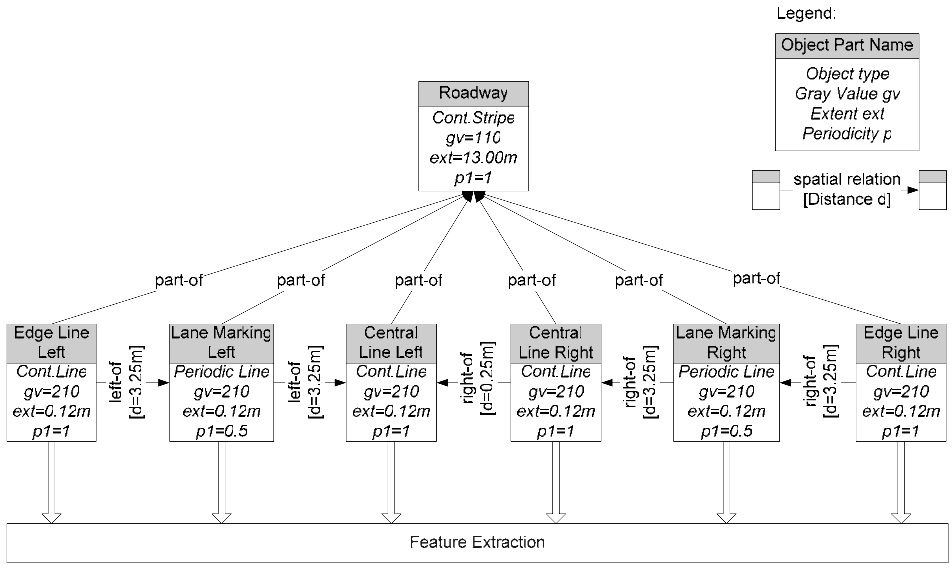


Figure 6. Concept Net for Dual Carriageway at Largest Scale, Generated for Images with Ground Pixel Sizes of 3.3 - 7 cm/pel

Figure 7. The Simulated Object Parts in the Original Scale

Target scale $\sigma_{t1} = 25$

In the decomposition phase every pair of adjacent line-type object parts in the lowest hierarchy level is investigated concerning interaction in the target scale. In case of interaction, the respective pair of lines is combined to a group of lines and those neighbouring lines are handled simultaneously and jointly in the scale change models. Otherwise, the object part is handled as a single line in the scale behaviour prediction phase.

For the scale parameter σ_{t1}=25 there is interaction between all neighbouring road markings in the target scale. Therefore, all object parts need to be combined to a group of lines formed by 6 lines for the example net. The image simulating the object parts in target scale as illustrated in Fig. 8 is derived from the synthetic image in Fig.7.

For this scale, Merging can possibly take place. Although interaction occurs for all line pairs, only for one line pair Merging can definitely be approved. The two central road markings are so close to each other that they exhibit a Merging in zone 3, as described in section 4.2, for this scale change. There is only a single maximum in the smoothed profile of this line pair left. For all other objects the test for Merging yields the "Domain of Uncertainty" (zone 2). For all these line pairs there are still two maxima isolating a single minimum detectable in the synthetic image simulating the target scale. Here, the operator is applied to the image to determine whether the other lines can be extracted separately in the target scale. In our example, for the extraction of all object parts the same feature extraction operator, the Steger operator [Steger98], is used, as all object parts are of line-type. We chose this operator because of its good performance and adaptability. The result shows no Merging of any of these line pairs with exception of the central line pair, since the operator is still able to detect all other lines separately. Note that the result depends strongly on the parameter set for the implementation of the operator, mainly on the hysteresis threshold values.

The possibility of Annihilations is detected by the calculation of the contrast in the target scale and if this result is in a range of 1 and 15, i.e. in the Uncertainty Zone for Annihilations, the feature extraction operator is applied to the synthetic image simulating the target scale. Definite Annihilations predicted by the calculated contrast below the smallest quantisation step were not found by the analytical analysis, but some of the predicted grey values fall in the interval for possible Annihilations depending on the feature extraction operator assigned in the initial net. Hence, the line extraction operator is to be applied again to the synthetic image simulating the respective combination of lines. From the result of the operator for this example, it can be derived that no Annihilations for the object parts have occurred.

The extent of the resulting line and the contrast is determined according to section 4.2. The attribute "Extent" is calculated from the position of the edges, which are determined empirically from the simulating image by searching for the maximal value of the line cross-section in the gradient image. For the merged object pair a shift of position has appeared in direction to each other. Generally, for two parallel lines with the same width and same contrast, the value of this shift equals half the distance of those two objects in the original scale. The periodicity stays unchanged, because the proportion of the gap and the line for the lane markings of periodic type, determined from the position of the edges of the line parts, stays the same in this example.

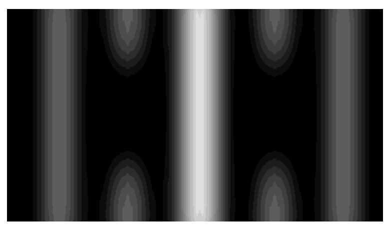


Figure 8. The Simulated Object Parts in the Target Scale σ_{t1}=25

In the phase of the fusion to a new semantic net, the spatial relations with their attributes concerning the lines' distances need to be adapted under consideration of the shift of position for the Merging pair. But the hierarchical relations and the spatial relations keep their type. The complete adapted semantic net for target scale σ_t = 25 is shown in Fig.9.

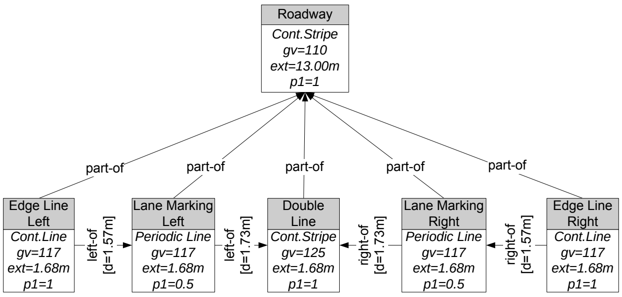
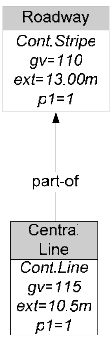


Figure 9. Adapted Semantic Net for the Target Scale σ_{t1} = 25

Target scale σ_{t2} = 100

The Gaussian filter used for the creation of the synthetic image of this scale is indeed very large with 500 pixels (about 5 times larger than the extent of a single lane of the road in the original resolution of 3.3cm). As can be expected interaction is predicted for all the object parts.

Fig.10. The Simulated Object Parts in the Target Scale σ_{t2}=100



In this scale all road markings are merged into one single remaining line (Fig.10). This object is barely visible due to its low contrast to the underlying pavement. In an image with only a bit stronger blurring, i.e. reduction of resolution, this object would disappear and only the road itself as one line will be left. This result is reasonable, since the road is only a little bit wider than the resulting merged line. The attributes are determined following the methodology of Section 4.2. The resulting semantic net in the coarser scale of σ_{t2} = 100 is illustrated in Fig. 11.

Fig.11 Adapted Semantic Net for the Target Scale σ_{t1} = 100

Due to representation reasons, the approach was demonstrated here only for fixed values of attributes in the nodes. Realistic object models would have ranges for the attribute values. If ranges are considered, the result has then possibly more than one semantic net as output in the target scale.

6. CONCLUSIONS

In this paper a methodology for the automatic adaptation of semantic nets composed of line-type object parts to any coarser scale was presented. The method enables the prediction of the appearance of object parts in small scale using means of differential geometry, while following the principles of linear scale space theory. In two examples for coarser scales the capability of the approach for the adaptation of a road model for a dual carriageway was demonstrated.

The presented object model describes only a special road type. But, in the near future, the methodology is to be augmented to variable road models in order to be able to represent different road types with the same model. The methodology, so far, does incorporate line-type features (lines and stripes) only. Intended is also the modelling of other objects on the road, such as vehicles, but also other types of road markings, such as zebra crossings and symbols. For these objects the scale space behaviour of area-type objects and their interaction with line-type features need to be examined. In addition, the implementation of this road model in the knowledge-based interpretation system GeoAIDA [Bückner01] is planned.

7. ACKNOWLEDGEMENTS

The work leading to this paper has been funded by the Deutsche Forschungsgemeinschaft under grant HE 1822/13.

8. REFERENCES

Baumgartner, A., 2003. Automatische Extraktion von Straßen aus digitalen Luftbildern. *DGK, Reihe C*, Dissertationen, No. 564, München, 91 p.

Bückner, J., Pahl, M., Stahlhut, O. and Liedtke, C.E., 2001. "geoAIDA - A Knowledge Based Automatic Image Data Analyser for Remote Sensing Data" CIMA 2001, Bangor, Wales, UK, June 19th-22nd 2001

Florack, L., Haar Romeny, B., Koenderink, J. and Viergever, M.,1994. Linear Scale-Space**.** *Journal of Mathematical Imaging and Vision*, vol. 4, no. 4, pp.325-251.

Hinz, S., 2004. Automatische Extraktion urbaner Straßennetze aus Luftbildern. *DGK, Reihe C*, Dissertationen, No. 580, München, 132 p.

Lindeberg, T., 1994. *Scale-Space Theory in* Computer *Vision.* Kluwer Academic Publishers, The Netherlands, 423 p.

Lindeberg, T., 1998. Edge Detection and Ridge Detection with Automatic Scale Selection. *International Journal of Computer Vision*, 30(2), pp. 117-154.

Mayer, H., 1998. Automatische Objektextraktion aus digitalen Luftbildern. *DGK, Reihe C*, Habilitation, No. 494, München, 131 p.

Mayer, H., 2000. Scale-Space Events for the Generalization of 3D-Building Data. In: *The International Archives of Photogrammetry and Remote Sensing*, Vol. XXXIII, Part B 4/2, Amsterdam, pp. 639-646.

Mayer, H. and Steger, C., 1998. Scale-Space Events and Their Link to Abstraction for Road Extraction. *ISPRS Journal of Photogrammetry and Remote Sensing*, 53, pp. 62–75.

Pakzad, K. and Heller, J., 2004. Automatic Scale Adaptation of Semantic Nets. In: *IAPRS*, Vol. XXXV, Part B3, Istanbul, 2004, pp. 325-330.

Steger, C., 1998. An Unbiased Detector of Curvilinear Structures. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(2), pp.113-125.

Steger, C., 1998a. An Unbiased Detector of Curvilinear Structures from 2D and 3D Images. *Dissertation*, Herbert Utz Verlag, München, 185 p.

Wiedemann, C., 2002. Extraktion von Straßennetzen aus optischen Satellitenbilddaten. *DGK, Reihe C*, Dissertationen, No. 551, München, 94 p.

Witkin, A., 1986. Scale space filtering. In Pentland, A. (Ed.): *From Pixels to Predicates.* Ablex Publishing Corporation, New Jersey, pp. 5-19.