# SCALE-DEPENDENT ADAPTATION OF OBJECT MODELS FOR ROAD EXTRACTION

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**ABSTRACT:**

The spatial resolution of available image data plays an important role at the creation of object models for road extraction. The type and perceptibility of roads changes with increasing ground pixel size. The design of the model for the extraction of roads therefore has to be influenced by the resolution of the available imagery.
In this paper we present a concept to automatically adapt road models for high resolution images to models suitable for images of lower resolution with similar spectral characteristics. The road model is formulated as a semantic net. Starting from the manually created semantic net for high resolution images and the given target scale, the road model is first automatically decomposed into groups of object parts. The representation of the object part groups in the coarser scale is then automatically predicted by scale change models, which are generated by deploying analytical as well as simulation procedures. The adapted object parts are at last fused back to a complete road model, which is suitable for road extraction in images of the lower target resolution.
The automatic adaptation of a semantic net to a coarser scale is demonstrated for a given model for road extraction. The presented adaptation methodology facilitates the creation of new models for automatic object extraction in lower resolution images.

## 1. INTRODUCTION

Landscape objects appear differently in images of varying spatial resolution. 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 same applies to the reduction of the resolution of an object of the same size – with increasing ground pixel size of the image the object will appear simplified with less detail until it disappears. 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 models for the object extraction have to be created for the same object. Generally, the information needed for the description of the object in low resolution is already contained in the object models[1] 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 exist an object model for high resolution images.

In this paper an approach to derive automatically models for object extraction for low resolution images from models created for high resolution images is presented. The object model for high resolution is here formulated manually as a semantic net, which ensures an explicit representation of objects and an intuitive creation process also for complex scenes. The focus for the investigated objects lies on line-type features, such as roads. The developed methodologies are presented here and tested exemplarily in this paper on a 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]. Also investigated has been the scale behaviour of line-type features [Steger98b, 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 short summary is given concerning the general strategy of the procedure. 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 the adaptation of a particular road model to a coarser scale. The last section gives a summary and draws conclusions from the presented work for future tasks.

[1] According to [Förstner93] different types of models in the image analysis process can be distinguished. The type of models we present and adapt here can be seen as an integration of both - object model and image model. The models not only describe the object in the real world with its object part hierarchies, but simultaneously contain the description for the appearance of the object parts in an image. In the remainder of this paper, these models are called 'object models'.

## 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).

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 and in neighbouring object parts that interfere each other's appearance in the coarser scale.

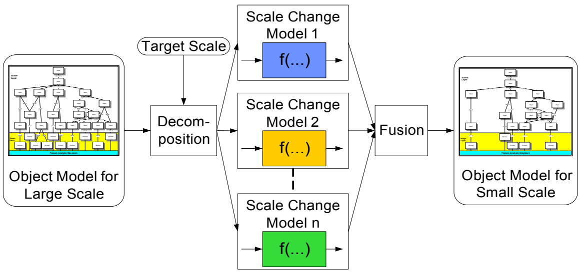


Figure 1. Strategy for Scale Adaptation

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 this single parameter any other level of scale can be described, while the original signal corresponds to $\sigma$=0. For the creation of another scale level, the original signal is convolved with the Gaussian kernel generated with the respective scale parameter $\sigma$. The one-dimensional Gaussian kernel is defined as follows:

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

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. Moreover, the causality criterion guarantees the non-enhancement of extrema and thus, every structure in larger scale must be invoked by a structure in the original signal.

Objects may interfere with each other as scale becomes coarser. According to [Lindeberg94] there are four events in two-dimensional discrete 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 number of object parts.
The line-type objects (lines and stripes) subject to our 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 remainder of this paper we will solely refer to lines.

## 4. METHODOLOGY

### 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:

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

In the two-dimensional discrete space (which applies to 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.

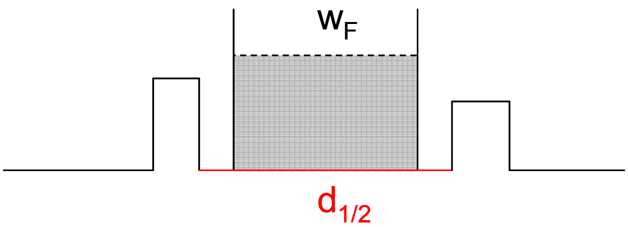


Figure 2. Dependency of Interaction between two Objects from the Filter Width and Object Distance

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.

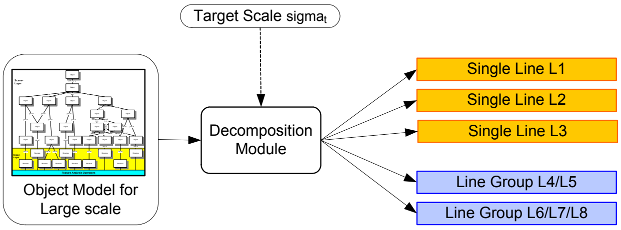


Figure 3. Decomposition of the Initial Object Model

### 4.2 Scale Change Models

For all object parts or groups that were sorted in the previous decomposition step, their appearance in the target scale is to be predicted by the scale change models. This task can in principal be solved 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 these events affect the type and number of the resulting object parts in the target scale.

**Merging**

In the case of a group of lines, the adjacent lines start at a certain scale, which is finer than the target scale, interacting with each other depending on their distance, as described above. Only interacting objects can be subject to the scale-space event Merging. Therefore, the possible case of Merging is only investigated for groups of lines. For a certain scale parameter $\sigma$ there will be two distinct maxima enclosing a single minimum in the profile of the lines (cf. Fig.4). With larger $\sigma$ 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 this zone 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 depicts 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 carried out by feature extraction operators attached to the nodes of the object parts. The characteristics of the operator determine the separability of objects and therefore the number of remaining object parts 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 (cf. Fig.4). This threshold can be found well by empirical analysis. The feature extraction operator, which is attached 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 in the target scale. The result of the operator applied to that synthetic image 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. If no feature extraction operator is specified, the number of resulting objects in target scale will stay uncertain. Due to the empirical analysis, the algorithm is very flexible, since the user's choice of the operator is free. The algorithm is also practicable, as there exist quite a few different line extraction operators and an analytical modelling of the scale behaviour of all relevant operators would exceed the realizable amount of work.

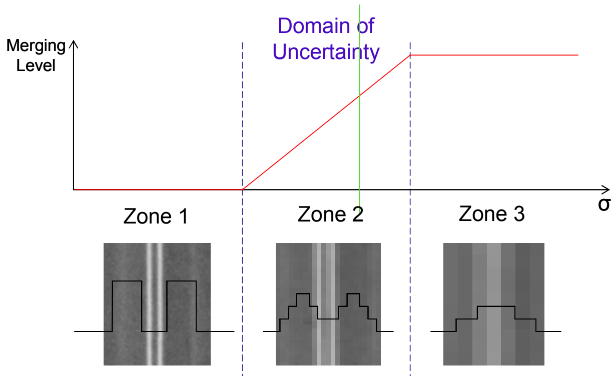


Figure 4. Merging Zones and Usability Threshold of the Feature Extraction Operator

To determine whether the target scale falls into the "Domain of Uncertainty" the line profile in the target scale is tested using differential geometry. By calculating the point of interaction and testing for definite Merging by searching for the existence of a minimum, the zone, in which the target scale is located, can be found.

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

**Annihilation**

According to [Steger98a] the responses of the convolution of the bar-shaped line profile $f_b(x)$ with width $w$ and contrast $c$ (notations as in section 4.1) with the Gaussian function $g(x,\sigma)$ can be calculated by:

$$r_b(x,\sigma,w,c) = f_b(x) * g(x,\sigma) \quad (3)$$
$$= \mathrm{c}(\Phi_\sigma(\mathrm{x}+\mathrm{w}) - \Phi_\sigma(\mathrm{x}-\mathrm{w})) \quad (4)$$

where

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

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 $\sigma$ is less 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 with 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 $\sigma_t$. The normalised value of the convolution integral determines the grey value of the line centre displayed in a discrete pixel matrix of the resulting image:

$$r(x,\sigma,w,c) = \frac{c}{\sqrt{2\pi}\sigma}\int_{x-w}^{x+w} e^{-\frac{t^2}{2\sigma^2}}dt \qquad (6)$$

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:

$$r(x=0,\sigma_t,w,c) < r_Q \qquad (7)$$

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 parameters, mainly on the threshold values. For a small contrast the occurrence of Annihilation depends on the operator. A realistic threshold for a grey value from which a reliable feature extraction operator should be able to detect a line can be set according to the individual character of the operator extracting the objects. Here again, if the calculated response of the convolution integral is below this grey value limit, the operator is applied to a simulating synthetic image and the result of the operator is used to determine the scale event.

The influence of noise may increase the grey value in the image. The threshold has therefore to be selected larger according to the expected amplitude of noise, if the influence of noise is to be included.

**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 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 points of the line profile in the target scale. The gradient in the direction perpendicular to the line has its largest absolute value at the position of the edge. However, the analytical examination with differential geometry for this problem cannot be solved straight forward [Steger98b]. Therefore, the edge positions are in the adaptation algorithm determined by using the gradient image with the corresponding target scale smoothing factor $\sigma_t$ 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 change, 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 deleted. For a Merging event the remaining number of objects is also reduced.

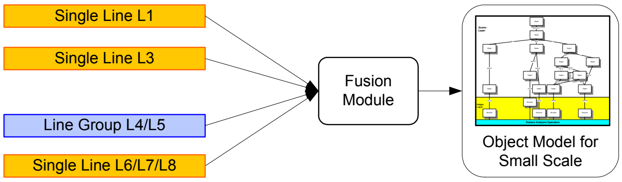


Figure 5. Fusion of the Object Model for Target Scale

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:

$$d_{\sigma_t L1,L2} = d_{L1,L1} - \frac{1}{2}\Delta w_{\sigma_t L1} - \frac{1}{2}\Delta w_{\sigma_t L2} + t_1 + t_2 \qquad (8)$$

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 (extent) 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 a created object model for roads are presented exemplarily. The methodology is applied to the slightly simplified object model for a dual carriageway introduced in [Pakzad&Heller04] suitable for images of high resolution (~5cm), 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). Note, that there is no extraction strategy explicitly contained in the model.

To demonstrate the capability of the developed methodology, the automatic adaptation is carried out for one target scale. As target scale $\sigma_t$=25, corresponding to a spatial resolution of about 2.6m, was chosen. The methods were implemented using the image processing system HALCON 7.0.

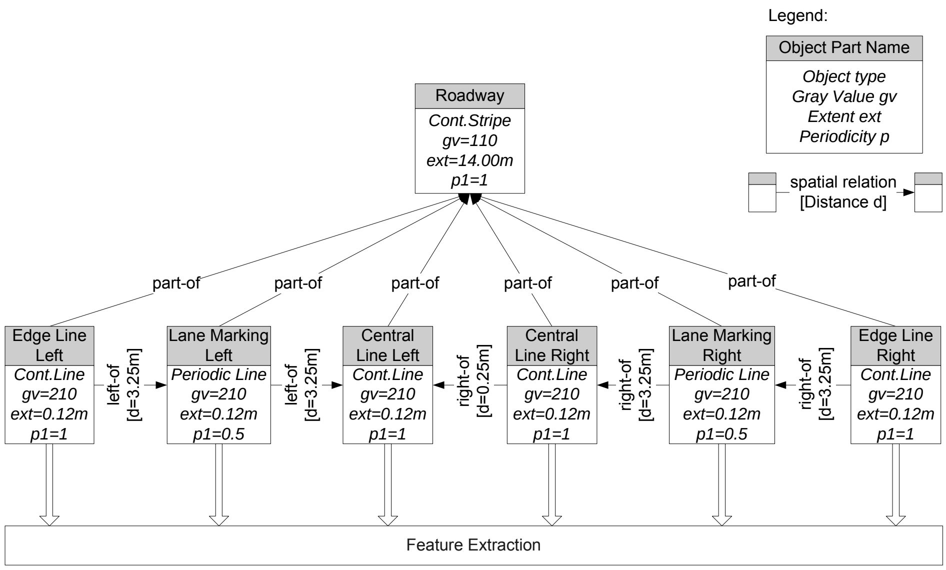


Figure 6. Concept Net for Dual Carriageway at Largest Scale, Generated for Images with Ground Pixel Sizes of ~5 cm/pel

A synthetic image for the simulation of 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). For the creation of this image information from the attributes of the nodes of the original semantic net were used. The contrast of the lines was deduced from the difference of the grey values of the road markings and the hierarchically higher node "Roadway" representing the road pavement.

Figure 7. The Simulated Object Parts in the Original Scale

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.

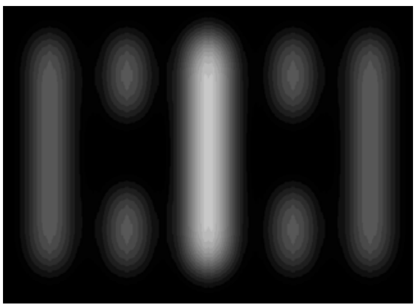

Figure 8. The Simulated Object Parts in the Target Scale $\sigma_t$=25

For the scale parameter $\sigma_t$=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 the 6 lines for the example net. The image depicting 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 of 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 [Steger98a], 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 parameters 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, which was set by us with the upper value of 15, the feature extraction operator is applied to the synthetic image of 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 target scale image with 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 positions of the edges, which are determined empirically 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. The gradient image for the synthetic image in target scale $\sigma_t$=25 is depicted in Fig.9.

Figure 9. The Gradient Image of the Simulated Object Parts in Target Scale $\sigma_t$=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 $\sigma_t$ = 25 is shown in Fig.9.

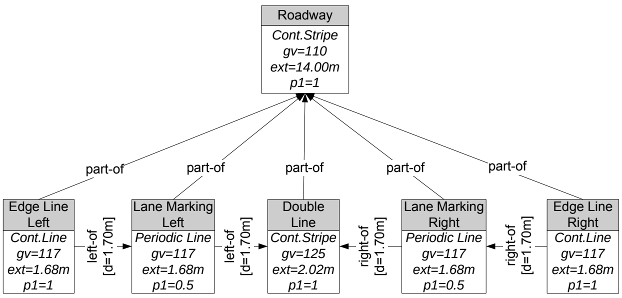


Figure 10. Adapted Semantic Net for the Target Scale $\sigma_t$ = 25

## 6. CONCLUSIONS

In this paper a methodology for the automatic adaptation of semantic nets composed of line-type object parts to a 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 one example to coarser scale reduction 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 type of roads. But, in 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 parallel 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 [Bückner02] is currently under progress and is expected to be finished soon. The developed methods for automatic scale-dependent adaptation are then to be verified by comparing the extraction results of the object models for high and low spatial resolution images.

## 7. ACKNOWLEDGEMENTS

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