SCALE BEHAVIOUR PREDICTION OF IMAGE ANALYSIS MODELS FOR 2D LANDSCAPE OBJECTS

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ABSTRACT:

This paper presents a new methodology for the automatic adaptation of image analysis object models for the extraction of 2D landscape objects to a lower image resolution. The knowledge of the object models is represented in form of semantic nets. The developed adaptation method includes a prediction of the object's behaviour in linear scale-space using analysis-by-synthesis. The scale behaviour prediction also takes into account scale events possibly occurring during scale change. The presented algorithm extends previous work concerning the adaptation of parallel linear object parts to object models consisting of 2D area object parts with arbitrary orientation. An example for the adaptation of an object model describing a 4-arm road junction with symbol markings demonstrates the application of the methodology. Finally, conclusions point out enhancements of the method.

1. INTRODUCTION

The appearance of landscape objects varies in aerial or satellite images of different resolution. Hence, for knowledge-based object extraction in images of different resolution, different models describing the objects are usually required. The objective of this paper is to introduce a new methodology for the automatic adaptation of image analysis models for object extraction to a lower image resolution. The objects that are modelled consist of 2D arbitrarily oriented object parts. The models for object extraction are represented as semantic nets. Since the image structure often severely changes between different image resolutions, the appearance of objects in lower resolution is to be altered by the adaptation method. The central problem is the prediction of the scale behaviour of object parts. The second core issue is the automatic handling of the given and adapted object model.

The method presented in this paper is an extension of work on the adaptation of object models consisting of linear parallel object parts [Pakzad & Heller, 2004; Heller & Pakzad, 2005]. The prediction of scale behaviour simplifies for linear-type parallel objects to a 1D problem, since an analysis of the cross-section is in principal sufficient. In the 2D case, which is tackled here, the scale behaviour of the objects is more complex. Particularly challenging is the prediction of 2D scale events that may occur during scale change.

We use linear scale-space theory for the prediction of the object's scale behaviour. The linear or Gaussian scale-space as defined first by [Witkin, 1983] and [Koenderink, 1984] is created by convolution of an image $L(x,y)$ with the Gaussian $g(x;t)$ of varying width. Thereby, a family of signals $L: R^2 \times R_+ \rightarrow R$ is derived depending only on a single scale parameter t corresponding to the square of the Gaussian standard deviation with $t=\sigma^2$. For more details concerning the characteristics of linear scale-space, see e.g. [Florack et al., 1994]. The analysis of image structure in different scales is also referred to as *deep structure* [Koenderink, 1984]. Two main approaches exist for the analysis of image structure in scale-space including the linking of 2D events between scales: the *scale-space primal sketch* proposed by Lindeberg [Lindeberg, 1993; Lindeberg, 1994] and the *scale-space hierarchy* suggested by Kuijper [Kuijper, 2002; Kuijper et al., 2003]. While the scale-space primal sketch is based on linking blob

primitives between adjacent scales, the scale-space hierarchy is constructed by linking critical points between scales. Since blobs are not only more stable and easier to track between scales, and linking of critical points between scales can also be ambiguous (and hence requires the determination of non-generic catastrophes) [Lindeberg, 1994], we developed a methodology for the automatic scale behaviour prediction of 2D object models based on blob linking.

In literature some other approaches dealing with scale behaviour analysis of landscape objects from remote sensing data can be found, e.g.: scale events for buildings were analysed in morphological scale-space by [Forberg & Mayer, 2002]; [Mayer & Steger, 1998] give an analytical analysis of the behaviour of a cross-section of a road with a vehicle in linear scale-space; the scale-space primal sketch was used by [Hay et al., 2002] for the scale behaviour description of whole landscapes as complex systems. However, the prediction of the scale behaviour of complete 2D image analysis object models and their adaptation to a lower image resolution is new.

The next section first summarizes the previously developed strategy for the adaptation of 1D object models and then gives an overview of the scale-space primal sketch. The third section deals with the requirements regarding the composition of automatically adaptable semantic nets. The adaptation method is outlined in section 4, while an example for the adaptation of a model for a junction area with road symbol markings is given in section 5. At last, conclusions finish this paper.

2. STATE OF THE ART

2.1 Scale-space primal sketch

The *scale-space primal sketch* was introduced by Lindeberg as an explicit representation of features in scale-space and their relations at different levels of scale [Lindeberg, 1993; Lindeberg, 1994]. The sketch provides a qualitative description of image structure and was designed as a basis for the extraction of significant image features at stable scales for later processing towards object extraction.

Blobs serve as primitives of the scale-space primal sketch. *Grey-level blobs* are smooth image regions that are brighter or

darker than the background and thereby stand out from its surrounding. Figure 1 illustrates the concept of grey-level blobs. By definition a grey-level blob $B(E)$ is a region of a scale-space image $L(x,y;t)$ associated with a pair of critical points (or regions in discrete scale-space) consisting of one local extremum E and one delimiting saddle S. The grey-level blob is a 3D object with extent both – in space and grey-level (indicated by z). The spatial extent of the blob is given by its *support region Supp(B)*. The grey-value of the delimiting saddle S equals the base level $z_{base}(B)$ of the blob. The support region of the blob is delimited by those points having grey-values exceeding or equal to the base level. On the other side, the volume of the grey-level blob $Vol(B)$ is defined by the integral of the image function over its support region. Finally, the blob contrast $C(B)$ is given by the grey-value difference of the base level $z_{base}(B)$ and the local extremum E. A sequential blob detection algorithm for the delineation of grey-level blobs in 2D discrete images using grey-value sorting initiated from local maxima serving as blob seeds is outlined in [Lindeberg, 1994].
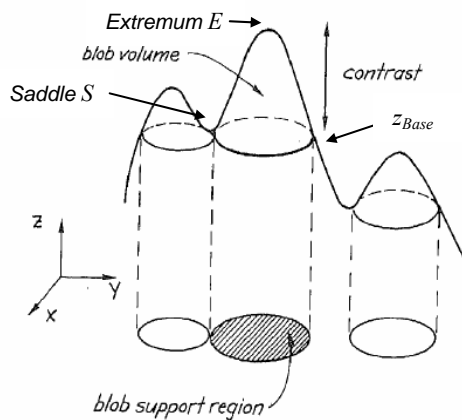

Figure 1. Definition of grey-level blobs (adapted from: [Lindeberg, 1993])

Generally, for a grey-level blob existing at a certain level of scale a corresponding blob at a slightly finer or coarser scale can be found. By linking these grey-level blobs between different scales so-called *scale-space blobs* are established. These four-dimensional objects have an extent in space, grey-level and scale. However, a plain linking of blobs between adjacent scale levels is not always possible, because scale events of blobs (blob events) induce topological changes in image structure between discrete scale levels. In terms of catastrophe theory, where scale acts as perturbation parameter, one of the two critical points of a blob – the local extremum E and the delimiting saddle S – is involved in a bifurcation [Lindeberg, 1992].

There are four types of blob events with increasing scale for 2D image structures to be distinguished:

- *Annihilation*: a blob disappears
- *Merging*: two blobs or more merge into a single one
- *Split*: one blob splits into two or more
- *Creation*: a new blob appears

Due to the singularities introduced by blob events in scale direction, the extent of a scale-space blob is delimited by the respective scale levels where the blob events occur. A scale-space blob is therefore associated with a scale-space lifetime, given by the difference of its appearance scale t_A and the disappearance scale t_D. In order to avoid ambiguous matching in the linking process of grey-level blobs between successive scales Lindeberg [1994] proposes an algorithm of adaptive scale sampling, which refines the scale sampling until all blob relations between adjacent scale levels can be unambiguously traced back to the four blob events. In this way, a complete scale-space representation of the image structure over all scales is derived. This information is desirable for the detection of significant image features in the most suitable scales, which complies with the aim the primal sketch was originally developed for. However, for the goal of our work – the automatic adaptation of object models to a given coarser scale – a complete description of behaviour over all scales is not required. Thereby, we introduce in section 4.2 a modified algorithm for the prediction of object appearance in a coarser target scale. This new method is inspired by the primal sketch and accomplishes blob linking between different scales.

2.2 Strategy and methodology of 1D adaptation

The scale-dependent adaptation of image analysis models describing objects composed of linear parallel object parts follows a process in three steps – decomposition, scale change analysis, and fusion. For details of the strategy see [Pakzad & Heller, 2004]. The same strategy (depicted in Figure 2) is applied in the adaptation procedure for 2D object models presented in this paper.
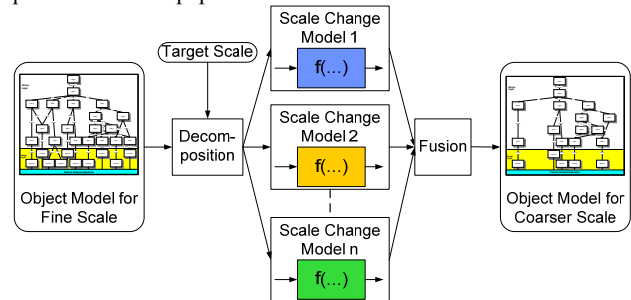

Figure 2. Strategy for adaptation process

The first stage of the automatic adaptation process decomposes the given object model for the fine scale into separate object parts that can be analysed separately regarding their scale behaviour. The decomposition takes into account the possibility of mutual influence of the appearance of nearby objects when scale changes – denoted as *interaction*. In this case, the respective object parts are analysed simultaneously in groups in the following scale change analysis phase.

Scale change models predict the appearance in the target scale for each interacting group or for single non-interacting object parts resulting from the decomposition. The prediction is carried out using analysis-by-synthesis, simulating the appearance of the object in the target scale by generated synthetic images.

At last, in the fusion stage all predicted object parts are recomposed back into a complete object model that is suitable for the extraction of the object in the target resolution. All hierarchical and spatial relations are maintained under consideration of the predicted scale events, which affect the resulting number of remaining object parts.

In contrast to the one-dimensional case, where only two scale events are to be considered, four different scale-space events may occur for 2D image structure, including the creation of new blobs with increasing scale (see also section 2.1). The prediction of scale events of participating object parts is thus not as straight forward and requires a more sophisticated approach to scale behaviour prediction than the previously presented method for linear parallel object parts.

3. COMPOSITION OF ADAPTABLE MODELS

The knowledge representation of the models for object extraction to be adapted automatically is realized in form of *semantic nets*. The concept of semantic nets allows the description of the individual parts of landscape objects in *nodes* and their mutual relations by *edges*. The object parts can be described in different layers: the real world, material and the image. The semantic nets we use for object description in this study describe the landscape object both in the real world and its appearance in the image. In the following, the reader is assumed to be familiar with semantic nets. For a review on semantic nets see e.g. [Niemann et al., 1990; Tönjes et al., 1999].

The concept of semantic nets enables many possibilities for the composition of an object model for the extraction of a particular object, i.e. the knowledge representation for the description of an object can be realized in very different semantic nets. Obviously, not all variations of semantic nets describing the same object are suitable to be treated in an automatic way. An automatic scale-dependent adaptation requires a few constraints concerning the composition of the given object model for high resolution. Details on necessary constraints concerning the generation of suitable semantic nets for the adaptation of linear parallel object parts are derived in [Pakzad & Heller, 2004]. Most of the previously formulated constraints for the adaptation of the 1D case in principal also apply to 2D objects. In particular, the requirements for the automatic decomposition of the given high-resolution semantic net and the assignment of a suitable feature extraction operator to each node must also hold for area-type arbitrarily oriented object parts.

Nevertheless, the additional dimension has to be considered in the given object models. The attributes in the nodes and edges have to deliver the spatial information concerning the appearance of the object in the image that is needed for the scale behaviour prediction in the analysis-by-synthesis process.
We define therefore the following attributes for nodes representing area-type object parts:

- Object Type: Objects with the same object type can be extracted by the same type of feature extraction operator. There are two categories for area primitives:
    - geometric object types: *rectangle, triangle, ellipse*
    - *arbitrary patterns* for more complex area-type object parts: its shape is defined by templates.
- Extent: The extent specifies the size of the object part and is stated in pixel numbers for the respective image resolution. For patterns the extent of the bounding box is relevant: its *length* and *width.* Geometric types are specified by their individual distinctive parameters.
- Orientation: This attribute is given in relation to the main axis of the object.
- Grey Value: This value describes the radiometric properties of the primitive.

The attributes of the spatial relations in the models are to be extended in comparison to line-type objects for specifications concerning:

- Distance: The value of the distance refers to a fixed point of the object acting as the origin of a local coordinate system. 2D objects require distance values concerning two perpendicular directions.

4. ADAPTATION METHOD

In this section the developed methodology for the three stages of the automatic adaptation process is explained in detail.

4.1 Decomposition

In order to facilitate the scale behaviour prediction of the object in the scale change models, a separate analysis of the individual parts of the modelled object is desirable. However, while scale changes adjacent objects may influence each other's appearance when they lie close to each other in the target scale. In this case, the participating objects need to be analysed together and form an *interaction group* in the successive scale change models. All other object parts that are not subject to interaction can be treated as single object parts in the scale behaviour analysis.

Whether interaction exists between object parts in the target scale depends on the distance of the respective objects and on the size of the Gaussian kernel associated with the target scale σ_t. As basis for decomposing the object parts in interacting groups or non-interacting single object parts, an *interaction zone* is established in form of a buffer surrounding each object part. If the individual interaction zones of (at least) two object parts intersect the respective object parts are assigned into an interaction group. Otherwise, the object part can be analysed separately as a single non-interacting object. The size of the buffer is determined by the size of the discrete Gaussian given by the target scale σ_t. Figure 3 sketches the concept of interaction zones.
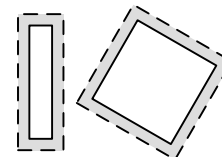

Figure 3. Interaction zones (grey, dashed border) around two nearby object parts (white, continuous border)

4.2 Scale change analysis

Scale change models predict the scale behaviour for each separate non-interacting object part and interaction group. The prediction is carried out in an analysis-by-synthesis procedure, analysing the objects in synthetic images in original scale, target scale, and target resolution. The analysis takes into account possible scale events of the object parts that may occur during scale change. The result is a description of the appearance of the object parts in the given target resolution in terms of attributes for the nodes and edges. The workflow of the analysis-by-synthesis process applied in the scale change analysis stage is depicted in Figure 4.

First, from the specifications of the object parts' appearance in the nodes of the given semantic net for the high resolution a synthetic image is created for each object part or interaction group to be analysed. This initial image L_0 simulates the appearance of the object parts in the original scale σ_0. In a second step, the initial image is transferred to the target scale σ_t by convolution with the respective discrete Gaussian into the target scale image L_t. The analysis regarding possibly occurred scale events is accomplished in this image. Since the prediction of the attributes describing the appearance of the object parts in the low resolution requires for the simulation a synthetic image in the target resolution, the target scale image L_t is subsequently down-sampled to the corresponding lower resolution R_t.
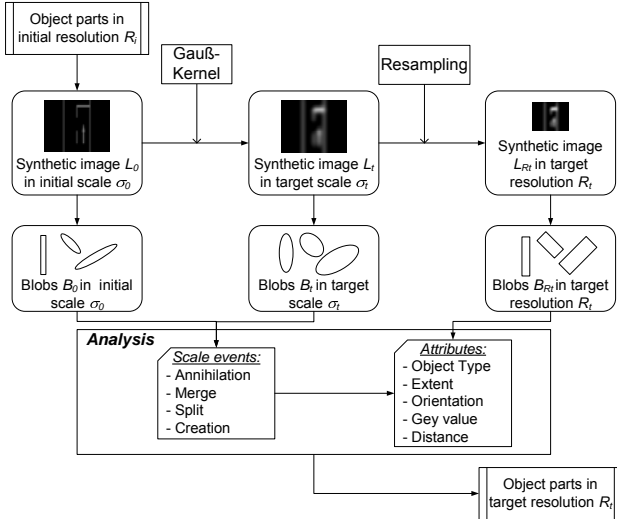
Figure 4. Analysis-by-synthesis process

4.2.1   Scale event prediction

The prediction of scale events considers the four possible blob events Annihilation, Merging, Split and Creation, as listed in section 2.2. However, the construction of a complete scale-space primal sketch over all scales is not necessary. Instead, for our goal – the adaptation of object models to a given lower resolution – the prediction of the number of remaining blobs in the target scale is sufficient. In accordance with the sampling theorem of signal theory, the total number of blobs in the target scale image corresponds to the remaining number of object parts in the given target resolution. Thus, only blob linking between the original and the target scale is necessary.

At first, blob detection is carried out in both the initial image L_0 and the target scale image L_t. The algorithm proposed for sequential blob detection in [Lindeberg, 1994] is used for this purpose. The results are the position of the support regions $Supp$ and the extrema E and saddles S of the blobs in both scales.

Blob linking between the initial image and the target scale image is then carried out by matching blobs with intersecting support regions in original and target scale. We use the support region of the initial scale as search space in the target scale and assume the target scale extremum not to drift outside its corresponding blob support region in initial scale. [Lindeberg, 1992] also states the observation that the blob support region acts as a coarse bound on the drift of local extrema. Although the drift velocity of local extrema may tend to infinity near a bifurcation (i.e. scale event), "the grey-level blob support region defines a natural spatial region to search for blobs in the next level of scale".

We assume that most blobs are not subject to a scale event during the scale change given by the specified target scale. In the blob linking process we thus first try to establish a so-called *plain link* between the initial and target scale for all blobs. Based on the number of blobs in initial scale $\#B_0=m$ of the set of support regions in initial scale $Supp_0$ and the number of blobs in target scale $\#B_t=n$ of the set of support regions in target scale $Supp_t$ a plain link must fulfil the following condition we define in this study:

Plain Link: One particular blob in initial scale has one and only one direct correspondence in target scale. The support region of a blob B_i in initial scale $Supp_0(B_i)$ intersects the support region of a blob B_q in target scale $Supp_t(B_q)$. All other blob support regions in target scale must not intersect $Supp_t(B_i)$.

$$\exists^{=1} q \ (Supp_0(B_i) \cap Supp_t(B_q) \neq 0) \quad (1)$$
$$, i \in \{1...m\}, q \in \{1...n\}$$

If a plain link cannot be established for all blobs, blob events must have occurred. The types of the respective scale events are then resolved for the remaining blobs. We therefore set up in this paper the following postulates for the occurrence of blob events during scale change:

Annihilation: One particular blob in initial scale has no correspondence in target scale. The set of support regions in target scale $Supp_t$ is empty at the position of a blob support region in initial scale $Supp_0(B_i)$.

$$\exists i \ (Supp_0(B_i) \cap Supp_t = 0) \quad (2)$$
$$, i \in \{1...m\}$$

Merging: Two (or more) initial blobs have one and the same blob as correspondence in target scale. The support regions of at least two initial blobs $Supp_0(B_i)$ and $Supp_0(B_j)$ intersect the support region of one and the same blob in target scale $Supp_t(B_q)$.

$$\exists q \ ((Supp_0(B_i) \cap Supp_t(B_q) \neq 0)$$
$$\wedge (Supp_0(B_j) \cap Supp_t(B_q) \neq 0)) \quad (3)$$
$$, i,j \in \{1...m\}, q \in \{1...n\}, i \neq j$$

Split: One initial blob has two (or more) blobs as correspondence in target scale. The support region of an initial blob $Supp_0(B_i)$ intersects the support regions $Supp_t(B_q)$ and $Supp_t(B_s)$ of at least two blobs in target scale.

$$\exists q \ \exists s \ ((Supp_0(B_i) \cap Supp_t(B_q) \neq 0)$$
$$\wedge (Supp_0(B_i) \cap Supp_t(B_s) \neq 0)) \quad (4)$$
$$, i \in \{1...m\}, q,s \in \{1...n\}, q \neq s$$

Creation: One particular blob in target scale has no correspondence in initial scale. The set of support regions in initial scale $Supp_0$ is empty at the position of a blob support region in target scale $Supp_t(B_q)$.

$$\exists q \ (Supp_0 \cap Supp_t(B_q) = 0) \quad (5)$$
$$, q \in \{1...n\}$$

4.2.2   Attribute prediction

The attributes in the nodes specify the appearance of an object part in the image. The values of the attributes in the nodes of the adapted semantic net for the lower resolution are therefore analysed in the synthetic target resolution image L_{Rt} simulating the object. Blobs correspond to the individual object parts. Hence, the number of blobs in the target resolution equals the number of nodes in the semantic net for the lower resolution. For each blob in the target resolution the following attributes are derived:

- Object Type: Due to scale events and deformations during scale change, the shape of primitives of exact geometric type may change significantly in the target resolution for a larger scale change. Instead, the shape of the object parts has to be described by an arbitrary pattern. Interacting patterns always lead to new patterns, which deliver new templates for the image analysis operators. These templates can be directly obtained from the analysis-by-synthesis process.

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- **Extent**: The support region of a blob serves as estimation of the respective object part's extent and position. The blob support region in target resolution $Supp_{Rt}(B)$ is delimited by its saddle point region S_{Rt}.
- **Grey Value**: The maximum grey value is determined for each blob in its previously determined extent (which is given by its support region).
- **Orientation**: As orientation is invariant with respect to scale change, the orientation of a blob only needs to be specified, if object parts are merged in target resolution. For this task, the main orientation of the bounding box spanning the blob is determined.

4.3 Fusion

The fusion is the last stage of the automatic adaptation process. All remaining nodes including their attributes representing the object parts in the given target resolution are compiled to a complete semantic net.

The hierarchical relations between the nodes remain unchanged as long as no scale event occurred. In case of Annihilation, the respective node is simply omitted. For merged blobs only a single *part-of* relation remains. For the Split and Creation events new *part-of* relation are introduced into the respective hierarchy level.

The type of the spatial relations stays unaffected. However, the distances between the object parts are to be adapted. The adapted distance values are derived from the position of the borders of the blobs support regions $Supp_{Rt}$ in target resolution.

5. ADAPTATION EXAMPLE

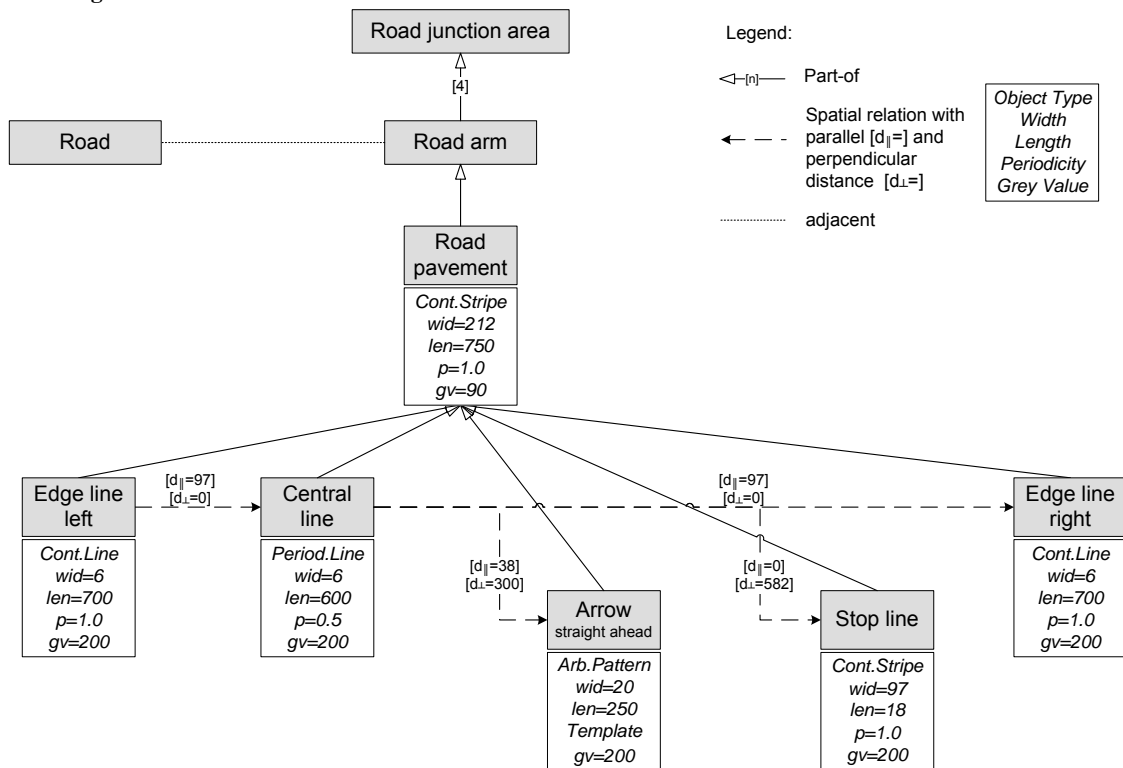### 5.1 Model in high resolution

Figure 5. Object model for junction area in a resolution of 0.03-0.05m/pixel

In order to demonstrate the applicability of the adaptation methodology, this section gives an example. A semantic net for the extraction of a 4-arm road junction with 2D symbols (arrows and stop lines) serves as given model for high resolution (3-5cm per pixel). We chose $\sigma_t=15$ as target scale; corresponding to an approximate target resolution of $R_t \approx 1.5$m. This junction model can be seen as a further development of work on road models consisting of linear parallel object parts towards modelling a road network. The node for an adjacent *Road*, for instance, could be represented by the model given in [Heller & Pakzad, 2005].

The junction consists of four identical road arms with a dashed central line. These arms converge and meet at a right angle in the junction area. The junction area contains modified lane markings and additional traffic markings (in our example direction arrows and stop lines). The width of the road pavement is modelled here to be constant. The model assumes a constant roadway width until the junction centre. The 2D position of object parts, given by distances, start from the beginning of the junction arms in direction towards the junction centre. The model also contains information concerning the extent of its object parts, i.e. also the length and width of the linear object parts and of the bounding boxes for arbitrary pattern. Since the assignment of suitable image analysis operators is a requirement for the composition of adaptable models, cf. section 3, all modelled object parts in the image have connections to a particular image analysis operator. The operators for the object parts of type pattern use cross-correlation matching with provided templates, whereas the line-type objects use the road marking operators developed in [Heuwold, 2006]. The junction model for the high resolution is depicted in Figure 5.

5.2 Adaptation process

The scale behaviour prediction of the junction example is carried out in the scale change analysis stage by an analysis-by-synthesis procedure. In the scale change models the four junction arms are treated separately as long as the interaction of adjacent junction arms affects only a small zone.

The number of blobs in initial scale (5) differs from the number of blobs in target scale σ_t (6), suggesting the occurrence of a scale event: a Split event is detected for the right edge line. Here, the corresponding blob splits up due to the strong influence of the nearby arrow blob and the adjacent stop line. The results of the blob detection in the synthetic images of the initial and target scale, illustrated in Figure 6b) and c), reflect the postulated condition for Split events from section 4.2.1 – the two support regions $Supp_t(B_1)$ and $Supp_t(B_2)$ in target scale σ_t intersect the support region $Supp_0(B_S)$ of the splitted blob from initial scale and the initial extremum $E_{S,0}$ intersects both support regions in σ_t.

For all resulting six blobs the node attributes are derived from the target resolution image L_{Rt}, cf. Figure 6d): as object types there is one *Continuous Line* (left edge line) and five *Arbitrary Pattern*; their extents are given by the enclosing bounding boxes of their blob support regions $Supp_{Rt}$; the grey values are determined from the blob contrast in its extent. The distances as attributes of the spatial relations (edges) are derived from the position of the blob support regions for area primitives.
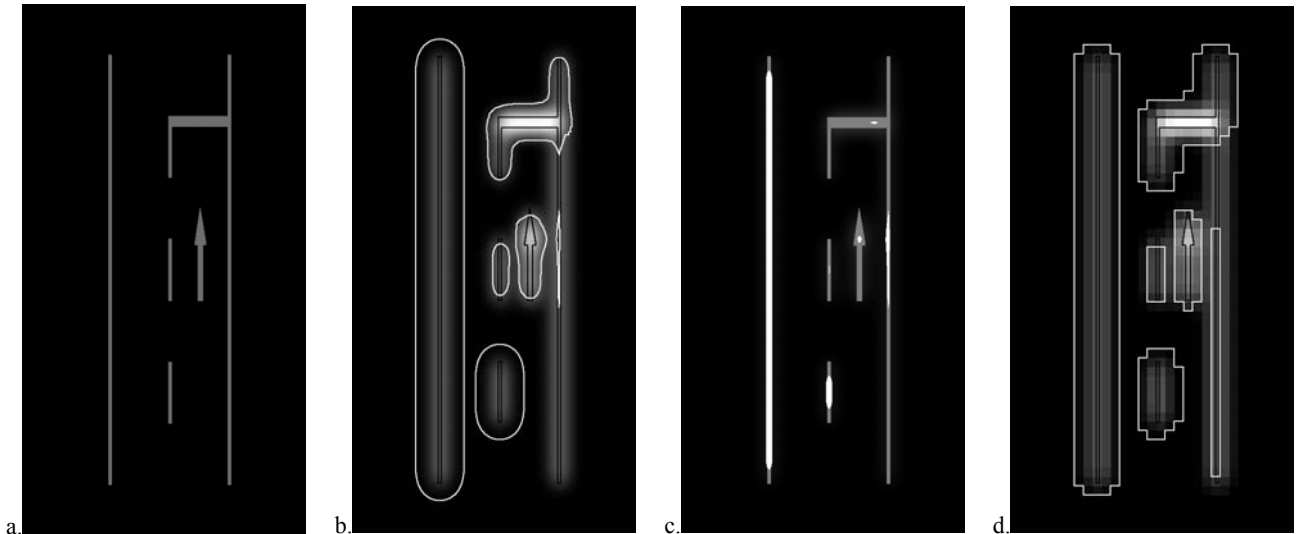

Figure 6. Blob detection results: initial blob features and target blob features superimposed on synthetic images; a. initial image L_0, b. support regions $Supp_0$ (black), $Supp_t$ (white) on target scale image L_t (grey-value stretched), c. extrema E_0 (grey), E_t (white) on target scale image L_t, d. support regions $Supp_0$ (black), $Supp_{Rt}$ (white) on target resolution image L_{Rt} (grey-value stretched and enlarged)

The adapted object model in the target resolution $R_t \approx 1.5m$ is illustrated in Figure 7.
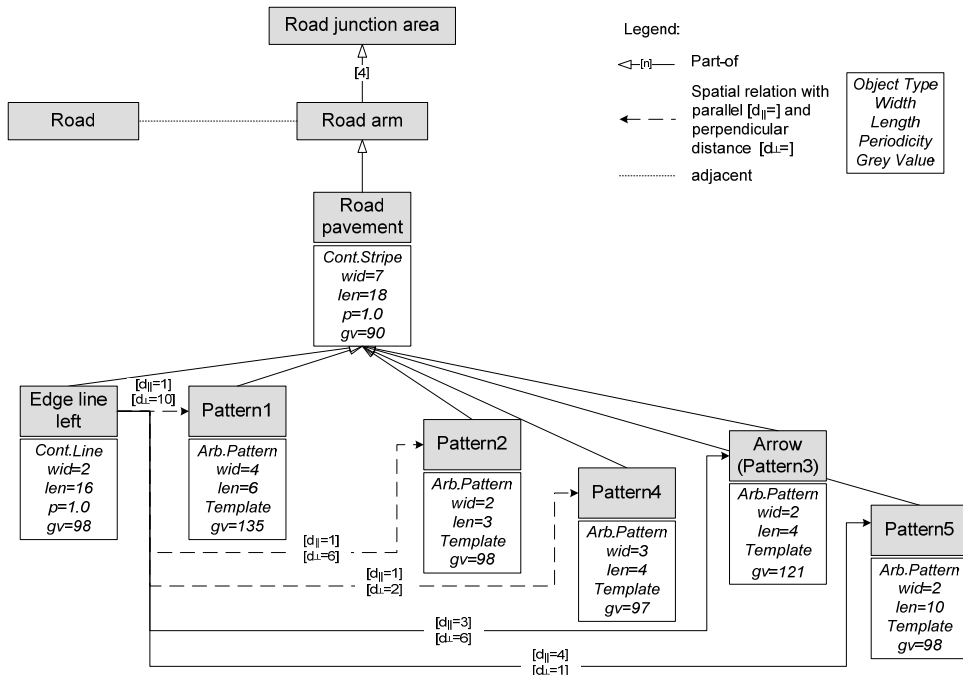

Figure 7. Adapted example object model in target resolution $R_t \approx 1.5$

6. CONCLUSIONS

In this paper a new methodology was presented for the automatic adaptation of image analysis object models, created for a specific high-resolution, to a lower image resolution. The modelled landscape objects can consist of arbitrarily oriented line-type or area-type object parts. In order to adapt the representation of the objects, the scale behaviour of the objects is analysed taking into account scale events and changes in the object's appearance.

The algorithm described here for 2D objects still needs to be verified for real image data by application of an example object model for high-resolution and corresponding adapted models for low resolution in a knowledge-based image interpretation system. Moreover, extensions of the methodology are planned regarding the flexibility of the adaptable models. The approach is to be extended for more realistic scene modelling, e.g. the adaptation of more complex image analysis operators for area-type primitives and the incorporation of relevant local context objects into the adaptation process.

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