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Scale-space events and their link to abstraction for road extraction

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Abstract

Abstraction, which is defined here as the increase of the degree of simplification and emphasis, is of major importance for object extraction. In this paper it is shown theoretically as well as empirically, how so-called scale-space events for lines define multiple abstraction levels for roads in images. The investigations are based on different scale-spaces as well as on a sophisticated model for line extraction for which the scales where events occur can be determined analytically. As one result of the investigations, a model is derived which is used in a multi-scale, multi-abstraction level road extraction system.

Keywords: image understanding; automatic road extraction; scale-space; abstraction

1. Introduction

There is much research in the area of road extraction from satellite and aerial imagery (Airault et al., 1994; Barzohar and Cooper, 1996; Grün et al., 1995). In small-scale imagery line extraction is of special interest. Line extraction is also important for large-scale images where road extraction can be done in multi-scales and multi-abstraction levels (Steger et al., 1995, Baumgartner et al., 1996). For the link of multiple scales and multiple abstraction levels theoretical considerations are given here.

Abstraction is only possible in a symbolic representation. The latter is in turn linked to knowledge representation (Sowa, 1995) where the description of single objects and their (spatial) relations are distinguished (Ullman, 1996). Together they can be used as *substructure*, i.e., parts, of more complex objects. Besides the fact that this constitutes a hierarchy of objects based on the part-of relation, there is also an *abstraction* linked to this. A settlement has, for instance, a substructure made of buildings, roads, etc. But, in addition, it also has a new, more abstract, quality, e.g., its own size or characteristics (shopping, recreation, etc.).

Whereas abstraction deals with symbols, scale-space theory (Koenderink, 1984; Lindeberg, 1994) is concerned with sub-symbolic image information. The standard procedure is that a scale-space is constructed by smoothing the original image with Gaussian kernels of successively increasing width. There also exist other scale-spaces with different characteristics which can be advantageous for object extraction. A property of scale-space theory is that, in addition to the continuously evolving smoothing of

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the image, events (*scale-space events*) occur. These events change the structure of the image significantly.

An interesting question in this context is how the scale-space events are related to the abstraction of symbols describing objects in the image. By and large, two things can happen simultaneously when an image is transformed by means of smoothing from a larger to a smaller scale:

(1) The information content of the image is reduced by eliminating regions and edges: noise as well as meaningful information is removed due to scale-space events.

(2) The removal of meaningful information is synonymous with the elimination of substructure (parts) of objects and results in simplification. The interesting feature is that the loss of substructure often emphasizes the objects. If abstraction is defined as the increase of the level of simplification and emphasis, this is synonymous with an abstraction of objects.

This abstraction by means of smoothing will be studied using the extraction of lines to recognize roads as an example.

Related work from psychology hypothesizes that the human visual system represents information on multiple scales (Kosslyn, 1994). The interaction of a low-resolution image with a small high-resolution part of it (fovea) to make vision not only faster but also more reliable is presented in Califano et al. (1996). Scale and abstraction (representation space) in the context of image sequences was treated in Bobick and Bolles (1992). This paper is perhaps the closest to the one presented here.

After an introduction into abstraction and scale-space, the approach for the detection of lines and the determination of their width is presented. The scale-space behaviour of the line extraction, with special focus on scale-space events, is analyzed, a model for roads represented as a semantic net is derived from it, and conclusions are given.

2. Abstraction and scale-space events

2.1. Abstraction and models

There are many definitions for the term abstraction (e.g., Brachman, 1983). In this paper a special notion of abstraction is used. It is defined in the context of image understanding where symbols are mapped to portions of images. The description by means of the symbols has to be structured. Additionally, it has to be simplified, emphasis has to be laid on important things, and others have to be neglected. *Abstraction* is therefore defined as the increase of the degree of simplification and emphasis.

As has been shown in the introduction, this is also connected to parts which construct the *substructure* of an object. Because the notion of a term has to be defined to enable a sound reasoning, the part-of relation as well as the specialization and the concrete relation are defined in this paper in terms of semantic networks, following Niemann et al. (1990) or Mayer (1996b).

Simplification and emphasis are important characteristics of models which are used to achieve the mapping of symbols and image data. This means that abstraction is also an implicit but integral part of models, and models are the critical basis of image understanding. They can be considered as the 'theory' part of the theoretical framework of Marr (1982) as well as the conceptual level of the levels of knowledge representation of Brachman (1979).

Explicit models must be the foundation for every project in image understanding, because they can give reasons for deficits of an approach. Without an explicit model, i.e., if a system is only based on heuristics, no sound analysis of errors is possible, and therefore the development is hampered. The typical development will start with constructing a model from experience. The model is implemented and tested, and according to the arising problems the model is improved. This is done iteratively.

2.2. Scale-space events

The main idea of *scale-space* theory is the creation of a multi-scale representation by a one-parameter family of derived signals, where fine-scale information is successively suppressed (Lindeberg, 1994). Data, in this case images, are systematically simplified and finer-scale details, i.e., high-frequency information, are removed. The *scale parameter* $\sigma \in \mathbf{R}_+$ is intended to describe the current level of scale.

The representation at coarser scales $L_\sigma(x)$ is often derived by a convolution of the given signal

$f(x)$ with Gaussian kernels of successively increasing width σ

$$L_\sigma(x) = g_\sigma(x) * f(x) \tag{1}$$

where $g\colon \mathbf{R} \times \mathbf{R}_+ \backslash \{\mathbf{0}\} \to \mathbf{R}$ is the (one dimensional) Gaussian kernel:

$$g_\sigma(x) = \frac{1}{\sqrt{2\pi}\sigma} \mathrm{e}^{-\frac{x^2}{2\sigma^2}} \tag{2}$$

Another way to define a scale-space is in terms of mathematical morphology (Köthe, 1996). A comparison and integration of both scale-spaces together with an expansion to curvature diffusion were given for the so-called *reaction–diffusion* space in Kimia and Siddiqui (1993) and Siddiqui and Kimia (1996) where the reaction part expresses mathematical morphology. Here, some more details and experiences are given for the diffusion part. In Kimia and Siddiqui (1993) it was shown that for small σ the diffusion part corresponds to Gaussian smoothing. For larger σ the approaches diverge. In the Gaussian scale-space elongated narrow areas are smoothed as strongly as small compact areas with the same brightness. In the diffusion part of the reaction–diffusion space only the strongly curved small areas are smoothed away. This means that the form of an object and not its brightness is of prime importance for the reaction–diffusion space.

As can be seen in Figs. 1 and 2, the cars on the road disappear in both images when the images are strongly smoothed. Generally, the level of smoothing where this happens depends on the level of noise in the image as well as on the closeness to other objects. Specifically and more importantly, the elongated and therefore less curved objects are much less influenced by the curvature-dependent smoothing of the diffusion part of the reaction–diffusion space. These first experiments show a big potential of the reaction–diffusion space which will be further investigated. Presently, the main problem seems to be the integration into the approach for line extraction presented below. Therefore, the remainder of this paper deals with Gaussian scale-space.

To describe the structure in an image, so-called *blobs* as the (zero order) scale-space features can be used (Lindeberg, 1994). Blobs are smooth regions which are brighter or darker than the background, stand out from the surroundings, and are therefore closely linked to extrema in the image.

In the process of smoothing the image, four different discrete events can happen to a blob: annihilation, merge, split, and creation. Whereas split and creation are not too likely to occur (examples are given in Lindeberg, 1994), merge and annihilation of blobs are quite common. But blobs are only one means to represent the information content of an image. More commonly used representations are regions, edges, and lines. In a first approximation, most of the events which can happen to blobs will happen to regions, their delimiting edges, or also lines. Taking this into account the term *scale-space* event is used for the remainder of this paper, referring to events of regions, edges, and lines.

How abstraction can occur by means of change of scale, and how this is linked to scale-space events is shown in the following, using the extraction of roads as line-like objects from aerial imagery as an example.

3. Detection of lines and line width

In recent years progress has been made to extract (curved) lines from digital images (Lindeberg, 1996; Mayer, 1996a). This paper is based on a new sophisticated approach which uses the differential geometric properties of the image function. The filter based on this gives only a single response for each line. Furthermore, the line position can be determined with sub-pixel accuracy and the position of the edges can be determined reliably even when the brightness on both sides of the line is different. The approach has been described elsewhere (Steger, 1996a,b). Therefore only a brief summary is given. However, details that pertain to the scale-space analysis and to object abstraction are described more in-depth.

3.1. Detection of line profiles in 1D

Many lines in aerial images have a bar-shaped profile. The ideal line profile of width $2w$ and height h is given by:

$$f_b(x) = \begin{cases} h, & |x| \le w \\ 0, & |x| > w \end{cases} \tag{3}$$

This type of line occurs for many 'interesting' objects in aerial images, e.g., roads or rivers, since these

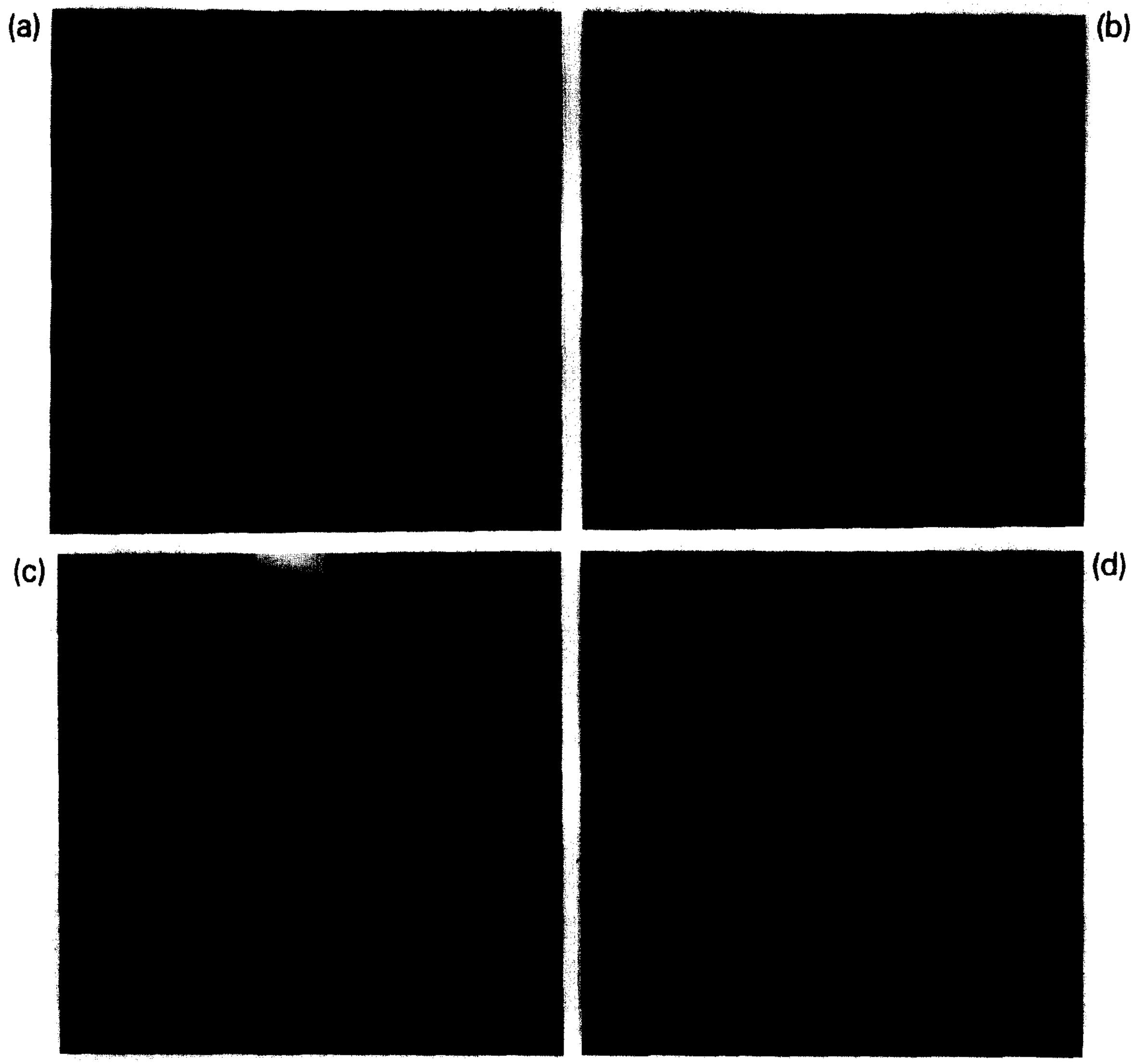

Fig. 1. Cars on road in Gaussian scale-space. (a) Input image; (b) σ=0.45 m; (c) σ=1.45 m; (d) σ=3.15 m.

structures often exhibit a relatively flat cross-section compared to the height of their edges.

In order to detect lines with a profile given by Eq. 3 the image should be convolved with the derivatives of the Gaussian kernel (Eq. 2). This leads to a description of the behaviour of the bar-shaped profile and its derivatives in scale-space ($r_b(x, \sigma, w, h)$, $r_b'(x, \sigma, w, h)$, $r_b''(x, \sigma, w, h)$).

To detect line points it is sufficient to determine the points where $r_b'(x, \sigma, w, h)$ vanishes. However, it is usually convenient to select only salient lines. A useful criterion for salient lines is the magnitude of the second derivative $r_b''(x, \sigma, w, h)$ in the point where $r_b'(x, \sigma, w, h) = 0$. Bright lines on a dark background will have $r_b''(x, \sigma, w, h) \ll 0$ while dark lines on a bright background will have $r_b''(x, \sigma, w, h) \gg 0$. When the scale-space behaviour of $r_b''(x, \sigma, w, h)$ is analyzed, it can be seen that the second derivative will not take on its maximum negative value for small σ. Furthermore, there will be two distinct minima in the interval $[-w, w]$. It is, however, desirable for $r_b''(x, \sigma, w, h)$ to exhibit a clearly defined minimum at $x = 0$ since the selection of salient lines is based on this value. It can be shown

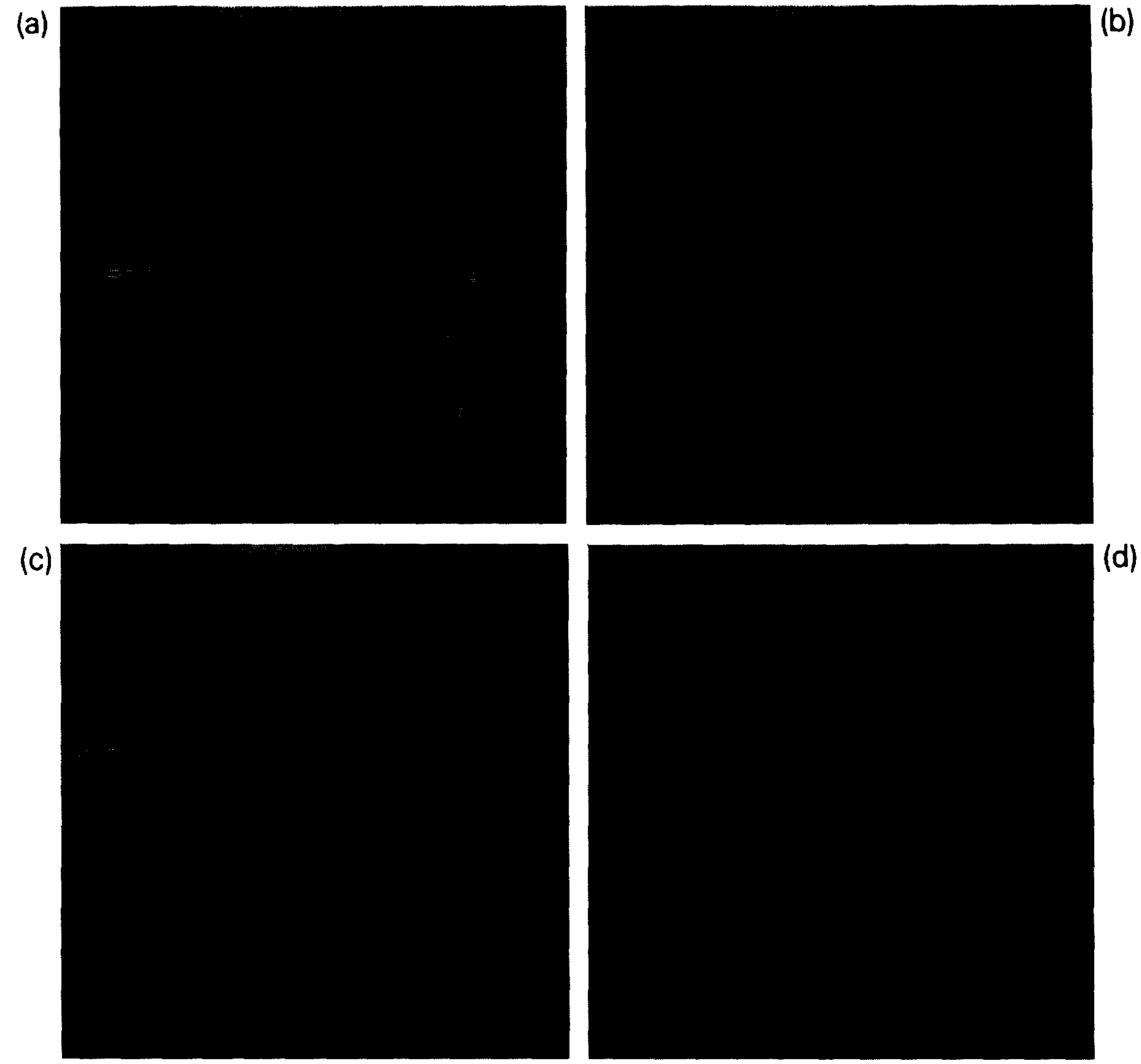

Fig. 2. Cars on road in diffusion part of the reaction–diffusion space — curvature radius (a) 1.5 m, (b) 3 m, (c) 9 m, (d) 15 m; input image see Fig. 1.

that

$$\sigma \geq w/\sqrt{3} \tag{4}$$

has to hold for $r_b''(x, \sigma, w, h)$ to exhibit a unique minimum, and $r_b''(x, \sigma, w, h)$ will have its maximum response in scale-space for $\sigma = w/\sqrt{3}$.

From Eq. 3 it is also evident that a line is bounded by an edge on each side of the line. Hence, to detect the line width the edge points to the left and right of the line point need to be extracted. Their position is given by the solutions of $r_b''(x, \sigma, w, h) = 0$, where $r_b'''(x, \sigma, w, h) < 0$, i.e., the points that exhibit a maximum in the absolute value of the gradient.

Fig. 3 shows the behaviour of the line and edge positions for a line with $w = 1$ and $h = 1$ for $x \in [-4, 4]$ and $\sigma \in [0, 4]$. It can be seen that the line position will always be in the correct place for all σ. The edge position, i.e., the line width, will be extracted most accurately for small σ; it will be extracted too large if σ is chosen too large for the desired w. However, the function which describes the relationship of the extracted line width and the true

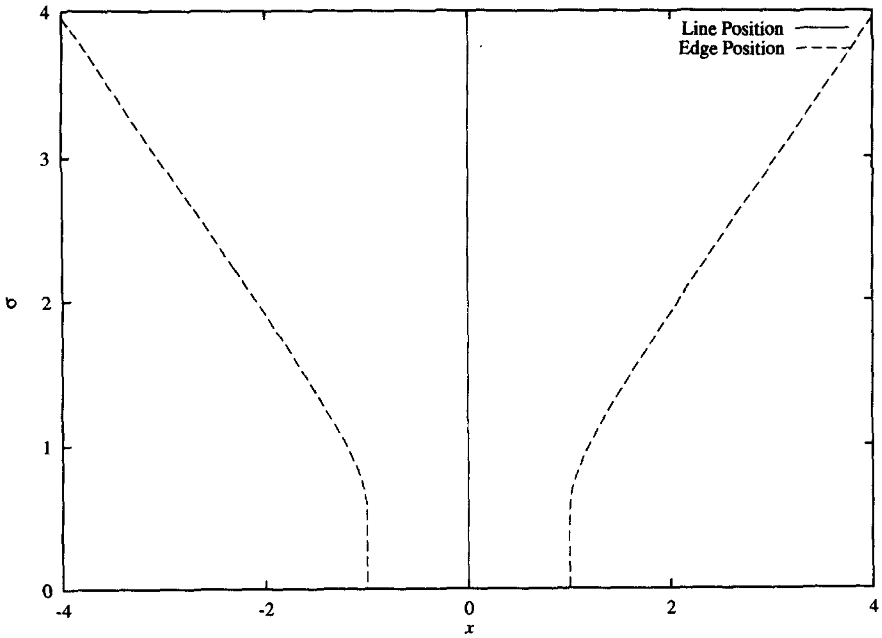

Fig. 3. Scale-space behaviour of the line and edge positions of the bar-shaped line with $w = 1$ and $h = 1$ for $x \in [-4, 4]$ and $\sigma \in [0, 4]$.

line width can be inverted. Therefore, it is possible to extract the true line width for all choices of σ.

3.2. Detection of lines in 2D

Curvilinear structures in 2D can be modelled as curves $s(t)$ that exhibit the characteristic 1D line profile f_b in the direction perpendicular to the line, i.e., perpendicular to $s'(t)$. Let this direction be $n(t)$. This means that the first directional derivative in the direction $n(t)$ should vanish and the second directional derivative should be of large absolute value.

The only problem that remains is to compute the direction of the line locally for each image point. In order to do this, the partial derivatives r_x, r_y, r_{xx}, r_{xy}, and r_{yy} of the image have to be estimated. This can be done by convolving the image with the appropriate 2D Gaussian kernels. The direction in which the second directional derivative of $r(x, y)$ takes on its maximum absolute value will be used as the direction $n(t)$. This direction can be determined by calculating the eigenvalues and eigenvectors of the Hessian matrix:

$$H(x, y) = \begin{pmatrix} r_{xx} & r_{xy} \\ r_{xy} & r_{yy} \end{pmatrix} \tag{5}$$

The eigenvector corresponding to the eigenvalue of maximum absolute value gives the direction perpendicular to the line. As in the 1D case, the second directional derivative along n, i.e., the maximum eigenvalue, can be used to select salient lines. To detect the width of the line, for each line point the closest points in the image to the left and to the right of the line point, i.e., along $-n$ and n, where the absolute value of the gradient takes on its maximum value, are determined.

4. The link of scale-space events to abstraction

4.1. Analytical investigation

Scale-space events and their link to abstraction can be analyzed in the same manner as the bar-shaped profile. Two lines that are close and approximately parallel to each other frequently occur in aerial images as the two road segments of a divided highway. The corresponding profile is given by:

$$f_d(x) = \begin{cases} 1, & v < |x| \le 1 \\ h, & 0 \le |x| \le v \\ 0, & |x| > 1 \end{cases} \tag{6}$$

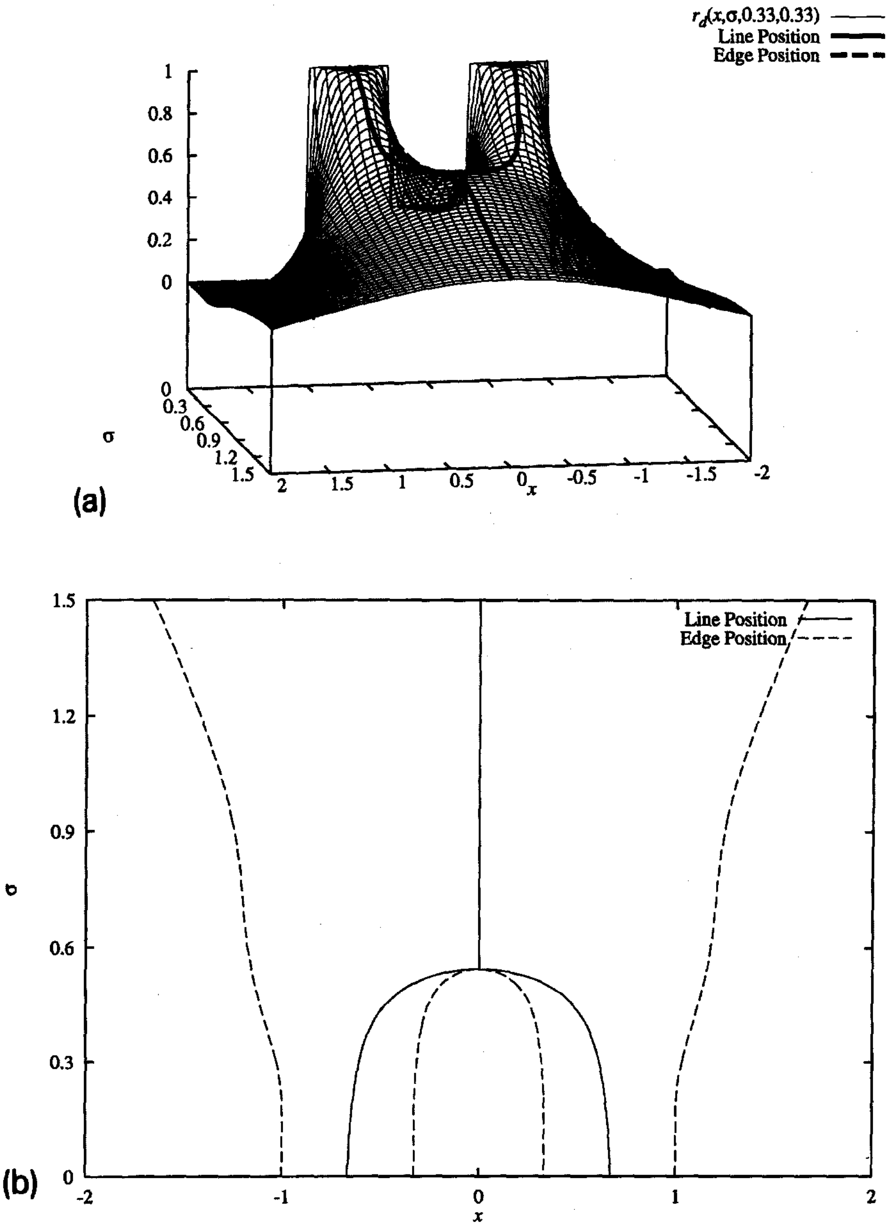

Fig. 4. Scale-space behaviour of two parallel lines. (a) Line and edge position in scale-space, (b) line and edge position.

It models two lines of the same intensity 1 and width $1 - v$ separated by a gap of width $2v$ and intensity $h < 1$. This results in no loss of generality since lines of arbitrary width can always be analyzed by multiplying the results obtained with this profile with the real width w. The same holds for any real intensity of the lines.

Fig. 4 displays the scale-space behaviour of the line and edge positions for a line of this type with $v = 0.33$ and $h = 0.33$, i.e., the lines and the gap have the same width and the gap is relatively dark. From Fig. 4a it can be seen that the gap between the lines will vanish as σ increases. Fig. 4b shows the line and edge positions of this smoothed profile. It is apparent that as σ increases the two distinct bright lines and the dark line in the middle will merge into a single bright line. At the same position the edge points between the two lines must vanish. For large σ only a single bright line will be extracted. It can be shown that the two lines will merge for

$$\sigma = \sqrt{\frac{1}{2}\frac{v^2 - 1}{\ln[(1-h)v]}} \tag{7}$$

This is important in two ways. First, this means that a scale-space event has occurred and Eq. 7 gives the exact σ at which the merge will happen. Second, it means that merely by increasing σ one can abstract two road segments into a more abstract highway. The location of the abstracted object will automatically reflect the centre axis of the entire highway.

Eq. 7 can be used to select an appropriate scale to ensure the merge happens or to prevent it from happening, depending on the application. A typical German three-lane highway has a total width of 37.5 m with a median strip of width of 4 m, which is usually relatively dark. If Eq. 7 is to be used, one has to set $v = 0.107$ and can select $h = 0.2$, for example. This means that the two lanes will merge at $\sigma = 0.45$, which corresponds to $\sigma \approx 8.4$ m. Therefore, in this case σ must be chosen from the interval [4.8 m, 8.4 m], where the lower bound is obtained from Eq. 4 if the two lanes are to be extracted as separate objects, and >8.4 m otherwise.

An event happens where an object on the line obscures a part of it, for example, when cars drive on a road or ships sail on a river. The object is typically not in a location symmetrical to the centre axis of the line. This can be modelled by the following profile:

$$f_o(x) = \begin{cases} 1, & -1 \le x < l \wedge r < x \le 1 \\ h, & l \le x \le r \\ 0, & |x| > 1 \end{cases} \tag{8}$$

For $h < 1$ the object is darker than the line, and for $h > 1$ it is brighter. Because the scale-space behaviour is somewhat simpler, only the latter case is considered here. For the other case similar results were obtained (Mayer and Steger, 1996).

Fig. 5 shows the behaviour for $l = 0.25$, $r = 0.75$, and $h = 1.5$. This models, for example, a bright car on the right lane of a road. It is intuitively clear that only one line should be detected for all σ, and this is indeed the case. Fig. 5a displays the line and edge positions mapped onto the smoothed profiles, while Fig. 5b compares them to the corresponding positions of an undisturbed profile. It can be seen that the difference is quite small. This means that the width correction mentioned in Section 3.1 will still yield meaningful results. For small σ the extracted line position will be the one of the bright object, while for large σ it will correspond to the centre axis of the line.

Therefore, by increasing σ one can eliminate the car from the road (scale-space event). It can also be seen that the two edges corresponding to the bright object will vanish along with the flat inflection points on the undisturbed part of the line. In general, the unwanted substructure will have vanished if σ is chosen according to Eq. 4. This means that the extracted line width will correspond to the true line width.

In summary, scale-space events often correspond directly to abstraction on a symbolic processing level. The locations of the abstracted objects correspond in a semantically meaningful way to the locations of the real objects. The analytical analysis of the model profiles allows the derivation of important scales (in terms of the sizes of objects) at which such an abstraction will take place.

4.2. Examples on aerial images

In this section, examples of the scale-space events discussed above are presented for aerial images to demonstrate that they are valid and meaningful, empirically as well as in theory.

Fig. 6a shows an aerial image with a ground resolution of ≈4 m containing a highway. Fig. 6b displays the results of extracting lines and their width with $\sigma = 5.6$ m. This results in the two lanes of the highway being extracted as two separate objects. A higher-level vision module would have to reason that the two lines are road segments, and would have to group them together as a single object highway. In contrast, Fig. 6c shows the results obtained with $\sigma = 18$ m. As can be seen, only the centre line of the highway is extracted. Thus, no further grouping is necessary to create the more abstract highway.

A different type of scale-space event is exemplified in Fig. 7a. Here, a road segment is disturbed

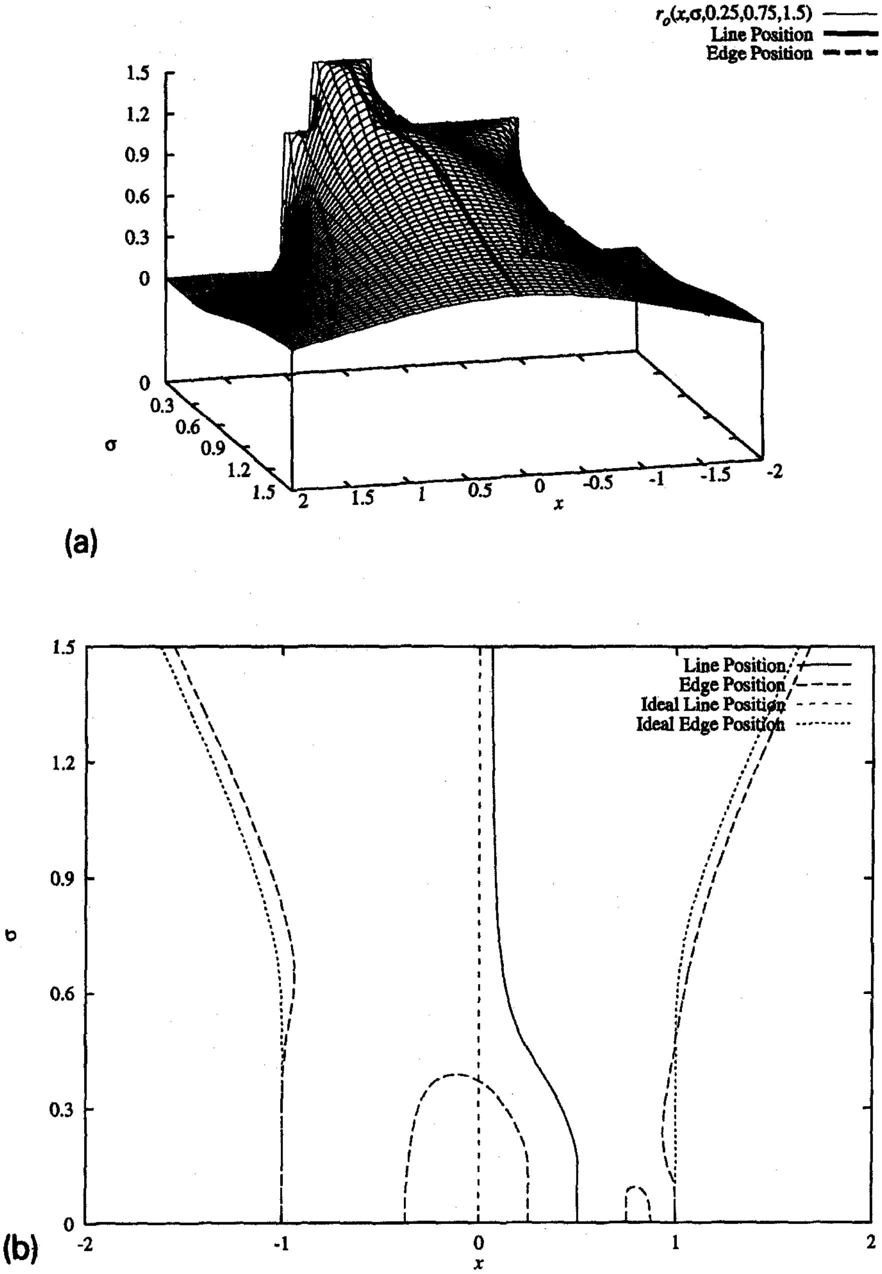

Fig. 5. Scale-space behaviour of a line with a bright disturbance on it. (a) Line and edge position in scale-space, (b) extracted and ideal line and edge position.

by substructure. Several cars, some of them brighter than the pavement, some of them darker, but all possessing large shadows, conceal the pavement. Moreover, the sidewalks are brighter than the pavement. This gives rise to a very complex scale-space behaviour. In Fig. 7b the results of extracting lines with a scale of $\sigma = 2.4$ m are displayed. This results in the extraction of several parallel and sometimes broken lines. Most notably, the van on the left side of the image gives rise to a separate line. Furthermore,

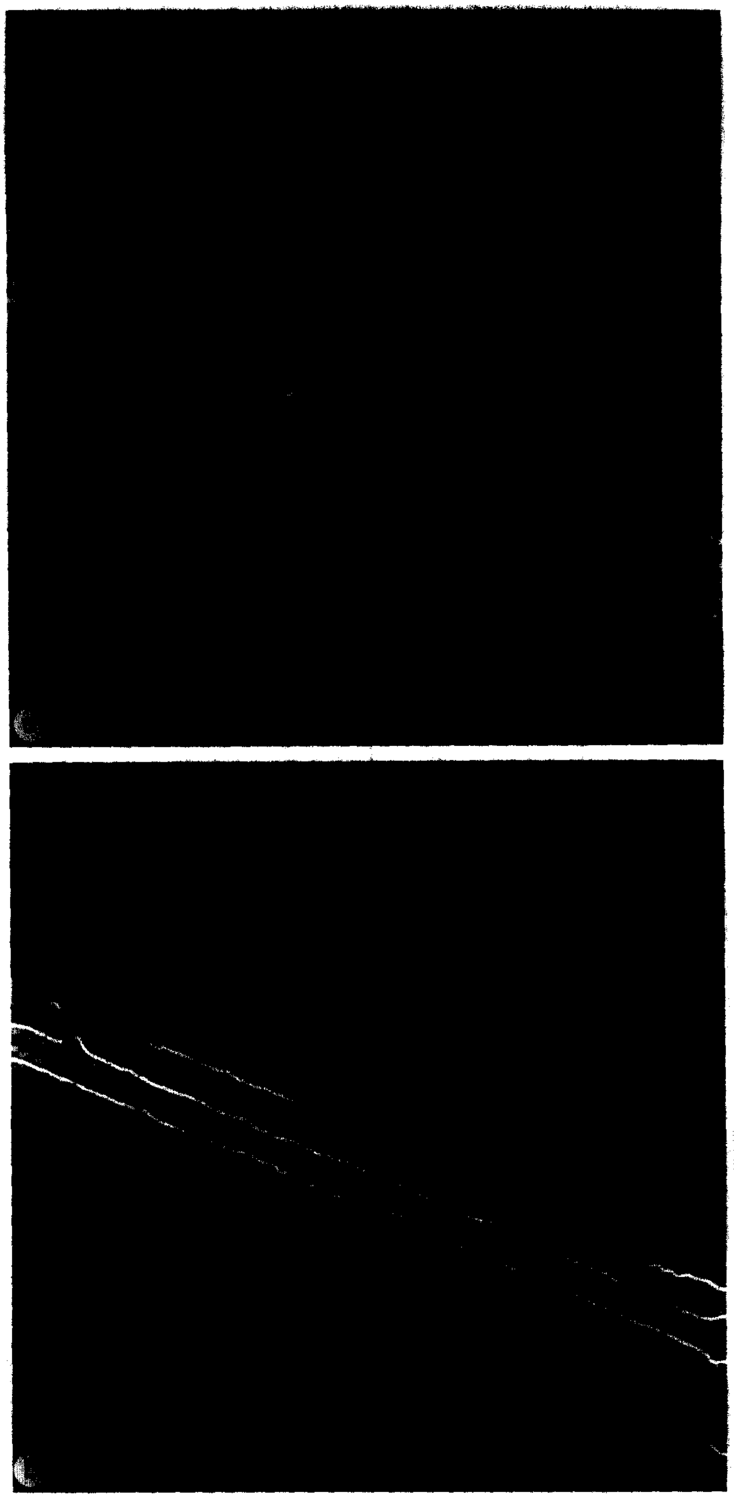

Fig. 6. Result of extracting lines (white) and line width (black) in an aerial image showing a highway. (a) Input image, resolution is 4 m, (b) σ=5.6 m, (c) σ=18 m.

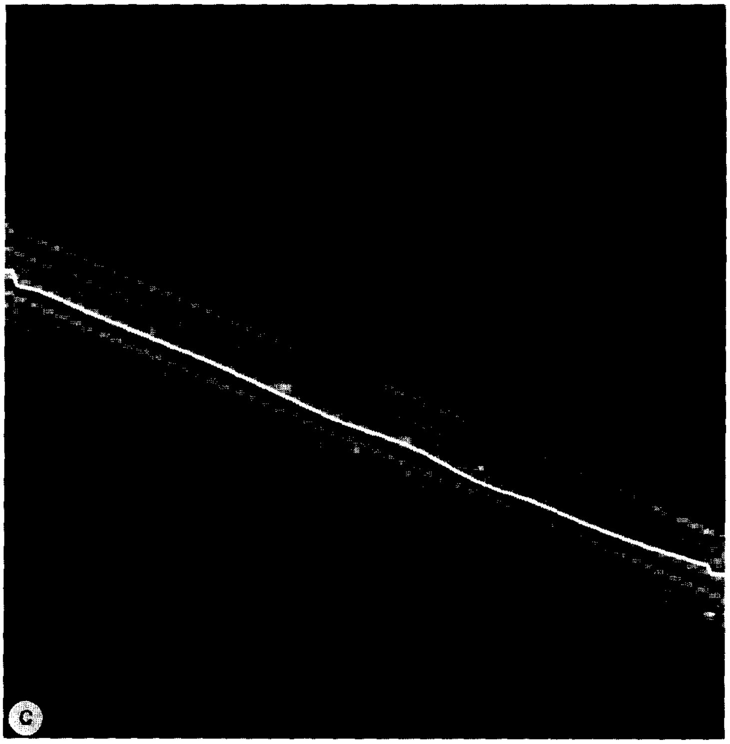

Fig. 6 (continued).

the sidewalks are extracted as separate lines since they form the dominant lines at this scale. If σ is increased to 5.6 m only a single line is extracted for the whole road. Because of the complex configuration of objects on the road the extracted position and width of the road is not perfect, but still very useful, as can be seen from Fig. 7c.

5. Model

From Section 4.2 it is evident that information is lost when going from large scale to small scale by eliminating regions and edges. In other words, the complex object highway of large scale is changed into a more abstract and stable linear road segment in

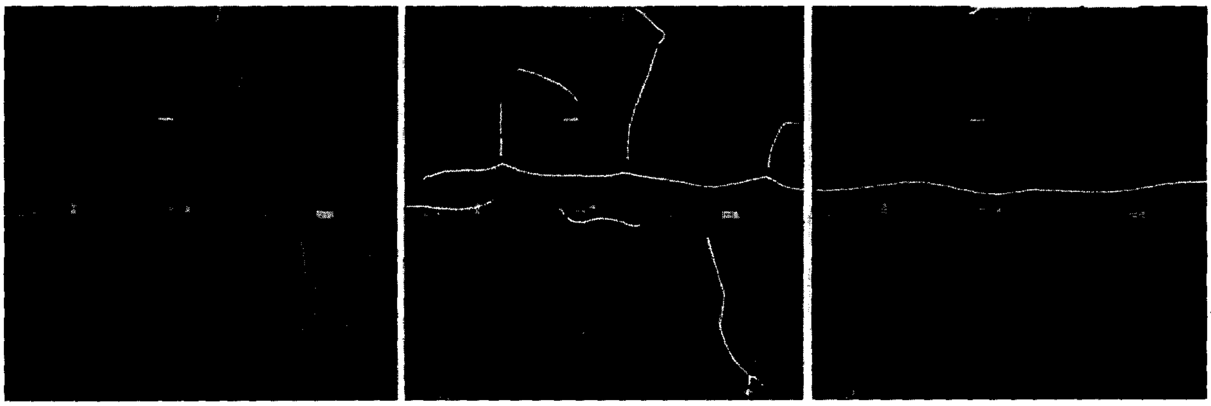

Fig. 7. Result of extracting lines (white) and line width (black) in an aerial image showing a road with several cars. (Left) Input image, resolution is 0.3 m, (b) σ=2.4 m, (c) σ=5.6 m.

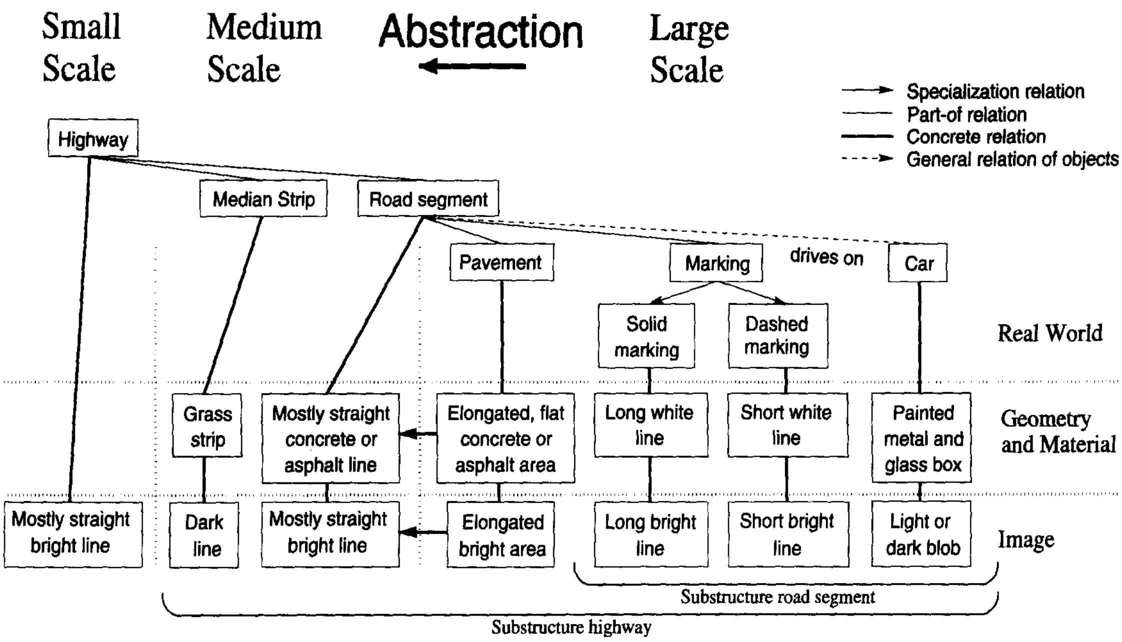

Fig. 8. Model for highway and road segment (concepts in boxes).

smaller scale. Abstraction has occurred by means of elimination of substructure (annihilation) and merge of different parts. In Fig. 8 the knowledge about the highway and the road segments is integrated into one model. The model is split into three levels. The *real world* level consists of the objects and their relations on a natural language level. In large scale a road segment is constructed of a pavement and the markings (solid or dashed). Cars drive or park on it.

The objects in the *real world* level are connected to the objects in the *geometry and material* level by means of the *concrete* relation which connects *concepts* describing the same object on different levels, i.e., from different points of view. The *geometry and material* level is an intermediate level which represents the three-dimensional shapes of objects as well as their material (Tönjes, 1996). This level has the advantage that it represents objects independently of sensor characteristics and viewpoint, which is in contrast to the *image* level.

With regard to scale the highway can be seen in the following way:

(1) The highway is in small scale linked to a mostly straight bright line in the *image* level which consists of the combined signal of the road segments and the median strip (cf. Fig. 6).

(2) In medium scale the highway consists of road segments and the median strip. The road segments are linked to mostly straight bright lines in the *image* level via the mostly straight concrete or asphalt lines in the *geometry and material* level. The median strip is linked to a dark line via the grass strip.

(3) In contrast to this, the pavement of the highway in large scale is linked to the elongated bright area in the *image* level by way of the elongated flat concrete of asphalt area in the *geometry and material* level. The markings are related to bright lines via white lines and the car is a light or dark blob as the concrete of a painted box made of glass and metal.

Conceptually, two things have happened by going from larger to smaller scale:

(1) The type of the geometrical representation has changed. Three lines have collapsed into one line. The elongated area has been condensed into a line.

(2) But, more importantly, the substructure of objects in the larger scale (the markings, or the car on the road for the large scale, or the median strip in the medium scale), has been eliminated.

This means that the complex object highway composed of median strip and road segment, which itself is made up of region-like pavements, and which has markings and cars on it, is changed into a more abstract object. Whereas the large scale gives the detail, the medium and small scale add global information. If the information of both levels is fused, false hypotheses for roads can be eliminated by using the abstract small scale information. Furthermore, details from the large scale (e.g., the correct width of the roads) are integrated into the result. Thus, the advantages of both scales are merged.

6. Summary and conclusions

This paper shows how the abstraction of concepts can be linked to scale-space events. This was studied on the example of line extraction, quantitative results were given and verified empirically. The results were then transferred to road extraction and a model for different scales was elaborated, which is the foundation for a successful system for road extraction from aerial images (Steger et al., 1995; Baumgartner et al., 1996). Furthermore it was shown that scale-spaces like the reaction–diffusion space have properties which can be of advantage for road extraction.

The outcome of this paper strongly recommends to use more than one scale for the recognition of objects. This not only has advantages in computational performance but, as was shown, the emphasis put on an object by smoothing away its substructure can be an important prerequisite for the recognition of objects ('only from a distance you can see clear'). A question which arises is the optimal scale to detect clues for an object. Small scales are especially suited for the detection of global structure and the formation of context (Strat, 1995) while large scales add detailed/specific information for a detailed classification or verification of objects. Analytical means to answer the question were given for the extraction of roads as lines.

In conclusion, a detailed analysis of the link of scale and abstraction of objects of an application (e.g., road or building), besides the question of context, could be one of the central issues of modelling in image understanding in the future. Problems which have to be answered are for instance the appropriateness of different scale-spaces. Here the geometric part which is handled by scale-spaces based on morphology or curvature diffusion, seems to play a role which is underestimated at present.

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References

Airault, S., Ruskoné, R., Jamet, O., 1994. Road detection from aerial images: a cooperation between local and global methods. In: Image and Signal Processing for Remote Sensing, Vol. 2315, SPIE, pp. 508–518.

Barzohar, M., Cooper, D.B., 1996. Automatic finding of main roads in aerial images by using geometric–stochastic models and estimation. IEEE Trans. Pattern Anal. Mach. Intell. 18 (7), 707–721.

Baumgartner, A., Steger, C., Wiedemann, C., Mayer, H., Eckstein, W., Ebner, H., 1996. Update of roads in GIS from aerial imagery: verification and multi-resolution extraction. Int. Arch. Photogramm. Remote Sensing 31 (B3/III), 53–58.

Bobick, A.F., Bolles, R.C., 1992. The Representation Space Paradigm of Concurrent Evolving Object Descriptions. IEEE Trans. Pattern Anal. Mach. Intell. 14 (2), 146–156.

Brachman, R.J., 1979. On the epistemological status of semantic networks. In: Associative Networks. Academic Press, New York, pp. 191–215.

Brachman, R.J., 1983. What IS-A is and isn't: an analysis of taxonomic links in semantic processing. IEEE Computer 16 (10), 30–35.

Califano, A., Kjeldsen, R., Bolle, R.M., 1996. Data- and model-driven multiresolution processing. Comput. Vision Image Understanding 63 (1), 27–49.

Grün, A., Agouris, P., Li, H., 1995. Linear feature extraction with dynamic programming and globally enforced least squares matching. In: Automatic Extraction of Man-Made Objects from Aerial and Space Images. Birkhäuser-Verlag, Basel. pp. 83–94.

Kimia, B.B., Siddiqui, K., 1993. Geometric heat equation and non-linear diffusion of shapes and Images. Laboratory for Engineering Man/Machine Systems, Division of Engineering, Brown University, Providence, Technical Report LEMS-124.

Koenderink, J.J., 1984. The structure of images. Biol. Cybernet. 50, 363–370.

Kosslyn, S., 1994. Image and Brain. MIT Press, Cambridge, 516 pp.

Köthe, U., 1996. Local appropriate scale in morphological scale-space. 4th Eur. Conf. Computer Vision, Vol. I, pp. 219–228.

Lindeberg, T., 1994. Scale-Space Theory in Computer Vision. Kluwer Academic Publishers, Boston, 423 pp.

Lindeberg, T., 1996. Edge detection and ridge detection with automatic scale selection. In: Computer Vision and Pattern Recognition. IEEE Computer Society Press, Los Alamitos, pp. 465–470.

Marr, D., 1982. Vision. Freeman, New York.

Mayer, H., 1996a. Extracting narrow linear structures from remote sensing images using search, global non-maximum suppression and resolution/scale integration. In: Mustererkennung 1996. Springer-Verlag, Berlin, pp. 374–382.

Mayer, H., 1996b. Using real world knowledge for the automatic acquisition of GIS-objects from scanned maps. GIS 9 (2), 14–20.

Mayer, H., Steger, C., 1996. A new approach for line extraction and its integration in a multi-scale, multi-abstraction-level road extraction system. In: IAPR TC-7 Workshop: Mapping Buildings, Roads and other Man-Made Structures from Images. Oldenbourg-Verlag, Wien, pp. 331–348.

Niemann, H., Sagerer, G.F., Schröder, S., Kummert, F., 1990. ERNEST: a semantic network system for pattern understanding. IEEE Trans. Pattern Anal. Mach. Intell. 12 (9), 883–905.

Siddiqui, K., Kimia, B.B., 1996. A shock grammar for recognition. In: Computer Vision and Pattern Recognition. IEEE Computer Society Press, Los Alamitos, pp. 507–513.

Sowa, J.F. (Editor), 1995. Principles of Semantic Networks — Explorations in the Representation of Knowledge. Morgan Kaufmann Publishers, San Mateo, 563 pp.

Steger, C., 1996a. An unbiased detector of curvilinear structures. Forschungsgruppe Bildverstehen (FG BV), Informatik IX, Technische Universität München, Technical Report FGBV-96-03.

Steger, C., 1996b. Extracting curvilinear structures: a differential geometric approach. 4th Eur. Conf. Computer Vision, Vol. I, pp. 630–631.

Steger, C., Clock, C., Eckstein, W., Mayer, H., Radig, B., 1995. Model-based road extraction from images. in automatic extraction of man-made objects from aerial and space images. Birkhäuser-Verlag, Basel, pp. 275–284.

Strat, T.M., 1995. Using context to control computer vision algorithms. In: Automatic Extraction of Man-Made Objects from Aerial and Space Images. Birkhäuser-Verlag, Basel, pp. 3–12.

Tönjes, R., 1996. Knowledge based modelling of landscapes. Int. Arch. Photogramm. Remote Sensing 31 (B3/III), 868–873.

Ullman, S., 1996. High-Level Vision. MIT Press, Cambridge, 384 pp.