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# AUTOMATIC DETECTION OF CHANGES IN ROAD DATABASES USING SATELLITE IMAGERY

**Dan Klang**
Department of Geodesy and Photogrammetry
100 44 Stockholm, Sweden
e-mail: dank@geomatics.kth.se

## ABSTRACT

An automatic procedure is developed for detection of changes between an existing road database and a newly registered satellite image, rectified to an orthophoto.
The approach uses the existing database to force the detection and delineation of the corresponding road network in the image. Each road segment is handled separately during the comparison between the image and the database as the position errors are considered to be randomly distributed along the road network. ”Ziplock snakes” are used to optimise the delineation process. The algorithm minimises, gradually, the internal and external energy sum represented by road bending respectively an eigenvalue of each image pixel calculated from the Hessian matrix formed by the partial derivatives of a Gaussian filter.
Logically new roads are connected to the existing network. Statistics from the image roads in combination with line linkage procedures form the method that generates the new roads supplementing the detected image roads.
Finally the comparison between the old road database and the roads detected in the image is performed. Changes are signalled if exceeding limits calculated from the variances of geometrical accuracy of the roads, internal image accuracy and the mathematical model of the orthophoto production.

## 1 INTRODUCTION

Road administration and other mapping agencies establish databases where a major part of the data are collected from existing maps. The position accuracy of the objects in the database is influenced by the digitalisation procedure as well as cartographic adjustments. Further, features stored in the Swedish road database, produced by the Swedish Road Administration, are positioned by measurements related to the nearest intersection. Geographical positions of each object has later been added but the position accuracy is still in need of improvement.

Manual detection and revision of changes in the existing road network and detection of new objects are time consuming parts of the database updating process.
A number of new applications such as route optimisation and car navigation increase the demands on actuality and high geographical accuracy of the road databases. Based on these interests much research in the area of road extraction from aerial and satellite imagery has been done (Airault et al., 1994).
The road updating problem can be divided into two main groups, identification and tracking (Grün et al., 1995). Usually the identification of start points is forced by an operator allowing an optimal localisation from an algorithmical point of view.
This semi-automatic approach of road delineation, where a human interaction still is needed, is the most convenient solution of tracking problems. Among them dynamic programming which finds the optimal path between two point and tracking algorithms, starting from a given point and direction (Vosselman et al., 1995), extrapolating new points, are established methods.
Snakes (Kass et al., 1988) and its extended version ”ziplock snakes” (Neuenschwander et al., 1995) are other ways of connecting node points. In (Li, 1997) Least-squares matching, based on artificial templates, are applied to the snake formulation.
A procedure for fully automatic detection of a complete road network is presented by (Mayer et al., 1998). By using a multi-scale approach, intersections as well as the road boundaries are detected in aerial photos.
The fact that roads in high resolution satellite imageries usually are just a few pixels wide, the advantages by parallel road boundaries and wide intersection areas in the latter reference could not be used. This disadvantage is compensated by using the database for initialisation during the delineation of each segment of interest.
As an alternative to the latter approach, the ”ziplock snakes” has been extended to be a fully automatic method using an existing road database. The location of node points, which in combination with the connecting road segment will serve as start values are given by nodes in the database.

A major problem during the automation of an updating procedure of existing geographical information is the lack of quality estimates of the data. An updating decision must rely on such estimates, else a manual evaluation is needed. This could be solved by a general estimation of the database features as well as the image position accuracy. Also high accuracy requirements of the extraction method, including the geometrical correction of the satellite images, are essential in the change detection procedure. Else not relevant changes in the database will be signalled as changes causing interpretation problem of the result.

## 2 CHANGE DETECTION MODEL

Generally, road databases are stored in a vector environment. GIS tools are preferably used to detect and extract features of interest for updating. As this research focuses on matching node points, road delineation and

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finally change detection between the original road network and the newly registered image, all roads are converted to a raster image allowing a software independent implementation.

As mentioned, previous work has exclusively focused on the semi-automatic approach, not taking existing road databases into account. An exception from the rule is presented in (Fiset et al., 1998) where a map-guided method is used to update the road network. The matching is conducted by using a multi-layer perceptron, also called backpropagation neural network, which is trained to recognise intersections and road segments in panchromatic SPOT images corresponding to the database features. The basic idea is similar to the approach in this paper where step one includes detection and matching between database and image intersections and dead ends. In the second step the delineation of the road segment is performed.

### 2.1 Locate node points

As road databases are assumed to include systematic as well as randomly distributed errors, sometimes gross, the automated node detection method and the delineation routine must take care of these type of discrepancies.
Intersections are usually the most reliable positions of the road network, independent of data collection method. In combination with the advantages during the matching procedure, these points stand out as the most advantageous alternative for node points.

The vector to raster conversion preceding this step allows for a simple node detection algorithm. As all vectors are converted to raster lines described by one pixels width, road elements could be declared in the following manner. If a road pixel is connected to 1, 2, or 3- pixels it is respectively defined as a dead end, straight line i.e. a road, and an intersection.

Gradually node pairs are located in the database. From each unprocessed node the connecting lines are followed reaching the next node point. Together with each of these connecting lines the two node points form a *road segment*. Matching templates are then created with the selected node located at the center of the area. An empirical investigation of optimal window size using the LSQ image matching method is in the size of 25*25 to 30*30 pixels and larger when affine parameters are used (Rosenholm, 1987).

The search area of the matching is defined by maximal expected deviation of the database in accordance to the correct geographical position, in this case represented by the orthophoto image.

### 2.2 Enhance image data

Road delineation using automatic matching requires that lines are separated from edge information in an automatic process. To optimize extraction of line information, the image is pre-processed using a 2-D Gaussian filter for choosing an appropriate extraction scale (determined by road width, pixel size, etc.) and also for noise reduction. Smaller kernels than 7*7 give too large noise influence.

The smoothed image derivatives, where $\sigma$ represents the smoothing factor,

$$g_{xx} = \sum\sum f(x+i, y+j) * h_{xx}(i,j) \tag{1}$$

$$g_{xy} = \sum\sum f(x+i, y+j) * h_{xy}(i,j) \tag{2}$$

$$g_{yy} = \sum\sum f(x+i, y+j) * h_{yy}(i,j) \tag{3}$$

$$h(i,j) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(i^2+j^2)}{2\sigma^2}} \tag{4}$$

are used in the Hessian matrix

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

for determining the curvature across the line feature. This curvature is estimated by calculating the eigenvalues of the Hessian matrix for each pixel of the search area image (Steger, 1996). The components of the eigenvectors giving the road direction, are used later on in the process when estimating the size of bendings along new roads. A large negative eigenvalue represents a bright line with a dark background, similar to most of the roads.
The goal of the filtering process is to achieve data where line information is represented in a more salient way than in the original image. High frequency areas, like urban areas, put other different demands on the filter than low frequency areas like those in the forest covered SPOT image (Klang 1997a).

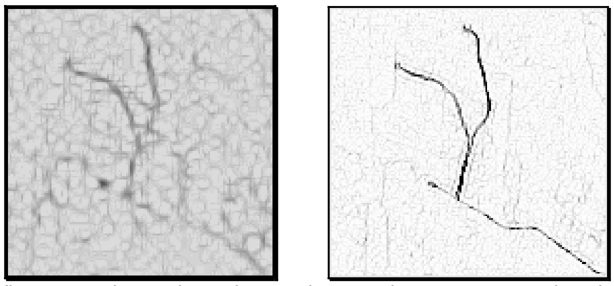

fig. 1-2. Enhanced Landsat and SPOT image, representing the maximal negative eigenvalues at $\sigma$ = 0.6. The original images are shown in fig. 4 and 5.

### 2.3 Match node point and enhanced image

Each node point and its neighbourhood, extracted from the road data image, form a matching template. The search image is represented by the largest negative eigenvalue of each image pixel. Different matching procedures, using the pre-processed template and search information, have been tested and evaluated (Klang, 1997b). An iterative least squares matching in two dimensions compensating for affine deformations and a cross correlation matching with subpixel position calculation gives almost the same result when the start

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value of the node is close to the solution.
Due to the earlier mentioned problem with randomly distributed errors, including small gross errors, only the cross correlation matching method remains as a possible solution. Scale space is normally used to match images where their geographical positions differ too much to reach correct matching in the original resolution. Roads in high resolution satellite images are usually 1-3 pixel wide which indicate the problem of using the scale space technique on such data.

As a correct detection of the node points is crucial for a successful delineation, a complementary solution is used to overcome local correlation peaks. If the maximal correlation of the two alternatives does not give the same pixel, the operator will be informed.
An alternative would be to use the ”interest operator” to detect the most salient point in an image including all correlation coefficients of the matching window (Förstner et al., 1987).

### 2.4 Calculate start values

The image positions of the two matched node points define the start and end points of the initial line prepared for the delineation process. The road segment, earlier connecting these two points, is divided in two parts. All pixels in the first part are shifted in accordance to the difference detected as result from the matching between the road database and the image position of the start node. The second part is handled in similar manner except that the calculation relates to the end node. The result of this process will be a road segment where the difference of the node shifts will be located in the middle of the segment. The following delineation algorithm will eliminate these discrepancies.

### 2.5 Match road segment and image

The overall problem to solve during a delineation process as for example road extraction is to achieve a balance between the curvature of the line and the intensity of the corresponding feature in the image. All previously presented methods intend to solve the complex problem, automatic balancing of two different types of measurements.

”Active contour models or snakes is an energy-minimising spline guided by external constraint forces and influenced by image forces that pull it toward features as edges and lines” (Kass et al., 1988). The approach has two key advantages (Fua et al., 1990). First, the geometric constraints are directly used to guide the search for a boundary. Second, the edge information is integrated along the entire length of the curve.
Active contours is a widely used concept for solving road delineation problems. Generally aerial images and a semi-automatic approach are used, allowing an interactive algorithm optimisation. If high resolution satellite imagery is used in combination with an existing road database, specific delineation problems will occur. The two main problems to be solved are to create sufficiently accurate start points and overlapping of occluded areas where parallel road edges don’t exist.

The active contour, as the original concept, can be described in parametric representation with

$$v(s) = (x(s), y(s)) \tag{6}$$

where s is proportional to the arc length and x and y are the curves coordinates.

The snake attracts to image features by minimising an integral measure representing the snake´s total energy, where the energy functional is:

$$E_{Snake} = \int_0^1 E_{Snake}(v(s))\,ds \tag{7}$$

$$= \int_0^1 E_{Internal}(v(s)) + E_{External}(v(s))\,ds$$

and in discrete form

$$E_{Snake} = \sum_{i=1}^{n} E_{Internal}(i) + E_{External}(i) \tag{8}$$

where *i* represents the equally distributed breakpoints of the line.

The internal energy makes it possible to introduce geometric constraints on the shape of the snake. Usually the energy depends on the intrinsic properties of the snake such as the length or curvature. The external energy depend on image structure, usually enhanced features of interest. Specific properties of the snake are normally derived from a suitable energy function and then the forces needed to reduce it are calculated. The internal energy, is usually based on the first and second derivative of the curve, constraining the snake to be a smooth curve. In the actual implementation the internal energy is represented as

$$E_{Internal}(v(s)) = (\alpha|v_s(s)|^2 + \beta|v_{ss}(s)|^2\ )/2 \tag{9}$$

and in discrete form

$$E_{Internal}(i) = \alpha|v_i - v_{i+1}|^2 + \beta|v_{i-1} - 2v_i + v_{i+1}|^2 \tag{10}$$

where $v$ stands for either x or y. $\alpha$ and $\beta$ are arbitrary functions to regulate the elasticity and bending. The derivatives of the first term, elasticity force, minimises the distance between the points and forces the snake to shrink. The derivatives of the second term represents the bending force, which will smooth the curve.

The external, image energy, can be defined as

$$E_{External}(v(s)) = -\int_0^1 P(v(s))\,ds \tag{11}$$

where $P(v(s))$ is a function where high values correspond to the feature of interest. Usually $P(v(s))$ is taken to be the magnitude of the image gradient, but in this

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implementation the maximal negative eigenvalues are used as image energy focusing on white linear structures.
The energy minimisation is solved using the *Euler-Lagrange* differential equation of motion with a discrete representation of the energies. The minimisation is solved iteratively until convergence is reached.
The external forces, defined by the derivative of the enhanced image features, and the discrete formulation of the internal forces are used during the minimisation procedure. In this implementation a combination of a resampling kernel and a derivative filter are used where a sub pixel value for each position in the filter can be achieved. This technique will increase the position accuracy of the snake.
While using an existing road database as start values during the minimisation, it is necessary to include a procedure to avoid the snake finding local minima not belonging to the road segment. The formulation of ”ziplock snakes” solves the problem by a gradual propagation from the end points toward the centre of the snake. The ziplock snake is divided into three parts by two *force boundaries* located at the vertices farthest away from the endpoints still feeling the image forces. The *active* and *passive* part of the snake are represented by breakpoints turned on respectively turned off, i.e. included or not in the minimisation. A realistic example of the iterative procedure is shown in figure 8.

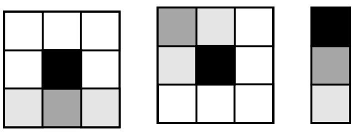
Each road segment located in the image is stored and the process continues until the entire image is processed. These ”image” road segments represent the geographical position of all roads already existing in the database.

### 2.6 Detect new roads

Logically new roads are connected to the existing network. Statistics from the image roads in combination with line linkage procedures form the method that generates the new roads, supplementing the already detected roads in the image.

Initially statistics, mean value and variance, are calculated using the eigenvalues of the road pixels detected during the previous road delineation. Seed points used for detection and delineation of new roads are extracted from the image using a threshold, calculated from the statistics. The procedure is optimised by dividing the image in smaller parts allowing an equal distribution of the seed points.

A simple line tracking algorithm, based on the eigenvalues and the direction of corresponding eigenvectors, is used.
The initial directions, forward and backward are calculated from the eigenvectors of each pixel. These directions are used as start directions. Next search area is related to the previous direction forced by the largest eigenvalue of the three neighbouring pixels in the selected direction.



Previous position
Suggested direction
Alternatives

$\alpha$ = 180° $\alpha$ = 315°
fig. 3. Linkage alternatives in two directions.

The linkage process results in a binary image with the centre line at the most significant line information, i.e. roads. Only those lines which are connected to an existing road are accepted.

### 2.7 Detect changes

Finally the comparison between the old road data base and the roads detected in the image is performed. Changes are signaled if the new position exceeds the square rot of the sum of the variances obtained from the geometrical accuracy of the roads, the internal image accuracy and the mathematical model of the orthophoto.

$$\sigma^2_{Boundary} = \sum(\sigma^2_{Road} + \sigma^2_{Image} + \sigma^2_{Model} + ......) \qquad (12)$$

## 3 TEST DATA

The test site is located in the middle of Sweden, outside Sundsvall, in a forestry area. Three different satellite data sources are available and partial used in the investigation. By using data from different sensors the robustness of the processes included in the model can be evaluated. Unfortunately the geometrical correction levels differ. The influences are small and not embarrassing for the evaluation.

Table 1. Test data set.

| Satellite | Band | Datum | Reg angle | Corr. | Res. |
|---|---|---|---|---|---|
| Landsat | TM3 | 950901 | Nadir | 2B | 10 m |
| SPOT | Pan | 950813 | +5.4 deg E | 2B | 10 m |
| IRS-1C | Pan | 970611 | Nadir | Ortho | 10 m |
| Road data | Topo | map | 1:50.000 | Ortho | 10 m |

Correction level 2B relates to the SPOT nomenclature. Level 2B is geometrically corrected with ground control points from topographical maps, the Swedish national grid RT90 including a Bessel ellipsoid. The resampling is performed in accordance with updated orbital parameters (Westin, 1991) and a flat DTM representing the mean elevation of the area. This technique minimises the influences of terrain variations. All data sources are resampled to 10 meters resolution making the matching procedure less complex, avoiding problems according to different resolutions.

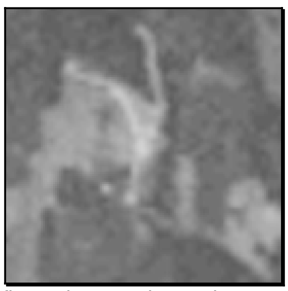


fig 4. Ljungaverk, Landsat
©ESA ©SSC Satellitbild

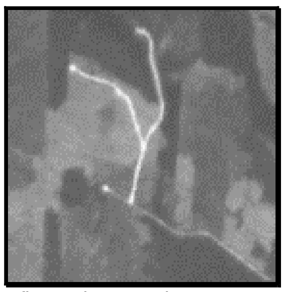


fig 5. Ljungaverk, SPOT
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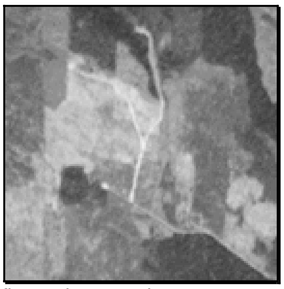

fig 6. Ljungaverk, IRS-1C ©Antrix ©Eosat ©Euromap

fig 7. Raster road data ©Lantmäteriverket

The entire road network is extracted from a topographical map, digital form, in scale 1:50.000. As all extracted roads are treated simultaneously in the change detection process, all roads are coded as level 255 in the rasterised road image.

## 4 RESULTS AND DISCUSSIONS

Node point matching, where the difference in geographical location exceed 2-3 pixels, requires alternative methods to overcome the problem with erroneous node positioning. A scale space alternative is tested. In case of differences the operator will be informed of the problem.

As the node points are used as start points of the delineation process, it is of great importance that they are correctly located. A global matching where the entire network is adjusted simultaneously will possibly increase the robustness.

The initial intention was to use the old road database to overcome problems with occluded or low intensity areas in the image. As the original snake algorithm uses image gradients to force the line closer to the image feature, start values of high accuracy are needed. The requirements are usually higher than what could be achieved from the road database, so an alternative approach is demanded. The ziplock snake overcomes the problem with inaccurate start values, but at the same time all non-active parts of the snake are recalculated, destroying what could be sufficient positions when the old points are activated later.

Figures 8 a-d describe the iterative process starting with the initial position of the road which includes systematic as well as randomly distributed errors. The rapid shift in the centre of the line in fig 8 b is caused by different shifts of the node points. Figure 8 d shows the result after the iterative process. In figure 8 c the line is described by different colours where white represents the active part of the ziplock snake while black parts still are passive.

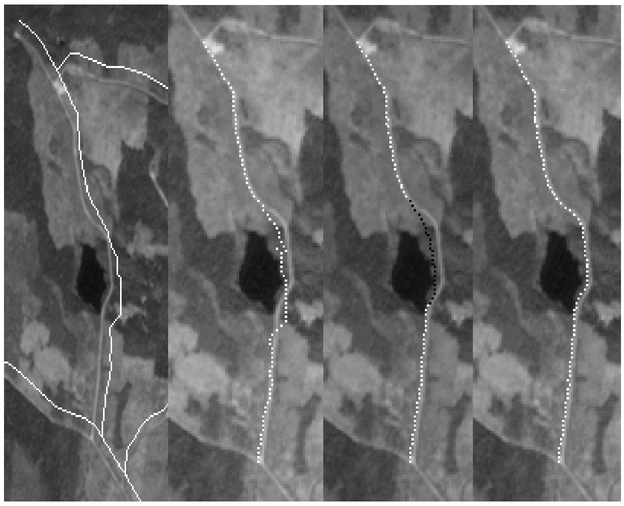

fig. 8 a-d Iterative ziplock snake procedure.

New roads are detected using a line linkage procedure, based on statistics from the old road network and its location in the image. The statistics are used to calculate a threshold relevant for roads in the local area. Each road pixel in the change detection image is represented by a grey value corresponding to its level of significance. The grey values are calculated using the eigenvalues from earlier processing.
All accepted lines are connected to the existing road network. A high level of acceptance of new roads involves signalling of irrelevant linear features, such as clear cut boundaries. This choice was made instead of a low level acceptance where some new features would not be signalled at all.

fig. 9. Change detection image. Solid white lines represents the old road database. Grey ribbons the new delineation of the old roads. New road pixels are represented by grey levels corresponding to their level of significance.

The change detection image in figure 9 shows the new delineation of old roads, represented by an acceptance boundary in grey. The delineation of old roads are shown in white and new roads in a greyish nuance representing different significance levels. This is not an optimal way of describing the changes, often a more efficient visualisation uses colour images or displays. The implementation includes this alternative.

## 5 CONCLUSIONS AND FUTURE WORK

High resolution satellite images with suitable resolution and accuracy and covering a wide area, allow a fully automatic comparison when the road database describes rural areas. Mapping urban areas demands higher resolution data, possibly generated from the next generation of satellites.

A big improvement will be achieved if GIS tools could be used to extract the node points and create templates from the vector database.

The cross correlation matching between the road database and the ortho corrected image is performed in a raster environment. A matching algorithm where the intersections and dead ends could be kept as vectors would probably increase the position accuracy.

A more robust node point matching based on a global pre-matching to detect gross errors is planned as an improvement of the existing technique.

Geometrical constraints will be added to the ziplock snake to increase the possibility to attract the vectors to features at far distance in the image.

The tracking algorithm will be further developed and tested on Landsat images. A possible solution is dynamic programming.

Position estimates of the image roads are needed for further comparison with the existing database. A complete automation of the updating procedure is impossible without a quality measure.

The task of signalling changes is also closely related to the need of quality estimates. If the data sources lack that information and a general quality estimate will be needed, the reliability of the signalled features will decrease.

## 6 REFERENCES

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

Fiset R., Cavayas F., Mouchot M-C., Solaiman B., Desjardins R., 1998. Map-image matching using a mult-layer perceptron: the case of the road network. ISPRS, Journal of Photogrammetry & Remote Sensing 53, pp 76-84.

Fua, P., Leclerc Y., 1990. Model Driven Edge Detection. Machine Vision and Applications, Vol 3, pp 45-56.

Förstner V., Gülch E., 1987. A Fast Operator for Detection and Precise Location of Distinct Points, Corners and Centres of Circular Features. ISPRS Intercommission workshop, Interlaken

Grün A., Agouris P., Li H., 1995. Linear Feature Extraction with Dynamic Programming and Globally Enforced Least Squares Matching. Automatic Extraction of Man-Made Objects from Aerial and Space Images. Monte Verità. Birkhäuser Verlag Basel.

Kass M., Witkin A., Terzopoulos D., 1988. Snakes: Active contour models. International Journal of Computer Vision, Vol 1(4), pp. 321-331.

Klang D., 1997a. Automatic extraction of line intersections for satellite scene orientation. The Royal Institute of Technology, Department of Photogrammetry, Stockholm, Sweden.

Klang D., 1997b. Automatic extraction of line intersections for satellite scene orientation. ISPRS Joint workshop, From Producer to User, Boulder, Colorado, United States.

Li H., 1997. Semi-automatic Road Extraction from Satellite and Aerial Images. ETH Dissertation No. 12101. Institut für Geodäsie und Photogrammetrie, Zürich, Switzerland.

Mayer H., Laptev I., Baumgartner A., 1998. Multi-scale and Snakes for Automatic Road Extraction. Computer Vision -ECCV´98, Volume I, pp 720-733.

Neuenschwander W., Fua P., Székely G., Kübler O., 1995. From Ziplock snakes to Velcro™ Surfaces. Automatic Extraction of Man-made Objects from Aerial and Space Images, pp 105-114, Basel, Switzerland, Birkhäuser Verlag.

Rosenholm D., 1987. Some Aspects of Least Squares Matching for Automatic Parallax Measurements. PhD thesis. The Royal Institute of Technology, Department of Photogrammetry, Stockholm, Sweden.

Steger C., 1996. Extracting lines using differential geometry and Gaussian smoothing. International Archives of Photogrammetry and Remote Sensing. Vol XXXI, Part B3. Vienna.

Vosselman G., de Knecht J., 1995. Road Tracking by Profile Matching and Kalman Filtering. Automatic Extraction of Man-made Objects from Aerial and Space Images, pp 265-274, Basel, Switzerland, Birkhäuser Verlag.

Westin T., 1991. On the Estimation of Interior and Exterior of SPOT Imagery. The Royal Institute of Technology, Department of Photogrammetry, Stockholm, Sweden.