INFORMATION-PRESERVING SURFACE RESTORATION AND FEATURE EXTRACTION FOR DIGITAL ELEVATION MODELS

Uwe Weidner *
Institut für Photogrammetrie, Universität Bonn, Nußallee 15, 53115 Bonn
Germany
e-mail: *weidner@ipb.uni-bonn.de*

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ABSTRACT:

Pre-processing such as filtering data in order to remove or at least reduce noise is a crucial step because information which is lost during this filtering cannot be recovered in subsequent steps. It is a well-known fact, that linear filtering does not only reduce noise, but may also lead to a loss of information due to the global smoothing, regardless of structures in the data. In order to overcome these drawbacks, we propose to use an algorithm for parameterfree information-preserving surface restoration. As we do not want to evaluate the results of the filtering only qualitatively by visual inspection, we examine the influence of pre-processing on feature extraction for digital elevation models and discuss quantities for the evaluation of these influences.

KURZFASSUNG:

Der Vorverarbeitungsschritt der Datenfilterung von beobachteten Daten zur Eliminierung oder zumindest Reduzierung des Rauschens erfordert, daß eine Glättung in homogenen Signalbereichen stattfindet, gleichzeitig aber auch die Information, die oftmals in inhomogenen bzw. unstetigen Bereichen des Signals enthalten ist, erhalten bleibt. Wird diese Information abgeschwächt oder gar eliminiert, so kann sie i. a. in späteren Schritten der Datenanalyse nicht wieder zurückgewonnen werden. Lineare Filterung kann bekanntermaßen nicht nur zu einer Reduzierung des Rauschens führen, sondern wegen der unabhängig von den in den Daten enthaltenen Strukturen globalen Glättung auch zu einem Informationsverlust an Unstetigkeitsstellen. Aus diesem Grund schlagen wir die Anwendung eines Algorithmus zur parameterfreien informationserhaltenden Flächenrestaurierung vor. Weiterhin sind wir nicht nur an einer qualitativen Bewertung der Filterungsergebnisse durch visuelle Kontrolle, sondern an einer quantitativen Bewertung interessiert. Daher untersuchen wir den Einfluß der Vorverarbeitung auf die Merkmalsextraktion für Digitale Höhenmodelle und diskutieren Größen zur Bewertung dieser Einflüsse.

1 INTRODUCTION

Digital Elevation Models (DEMs) are used for a variety of applications. Besides the classical applications for orthophoto production, mapping, and planning, DEMs are employed in the field of geosciences like hydrology and geomorphology. The former applications use DEMs in raster or triangle representation mainly for computations and visualizations, whereas the latter applications aim at extracting explicit information about the surface. Examples for this information extraction are the extraction of drainage networks in hydrology or the characterization of the relief and extraction of morphological structures in geomorphology. The main information about a surface is represented in surface specific structure lines. In case of a DEM these structure lines are e. g. ridge and valley lines.

The conversion from raster or triangle representation to features/structures which contain the information of the surface is an information condensation. This step condenses the implicit information represented by the raster or triangles to explicit information represented by the structures.

A number of algorithms for feature extraction have been proposed. All these approaches have in common that disturbances due to quantization or random measurement noise and unsignificant local pits or peaks affect their results. In order to overcome these problems, pre-processing to achieve an optimal data set for further feature extraction or a feature extraction algorithm which takes care of these disturbances is necessary. In many cases linear filtering is used for pre-processing. Linear filtering is fast and it removes or at least reduces the noise and generalizes the surface. Dependent on the filter width which has to be tuned by the operator, the result is a smooth surface everywhere, even at discontinuities, although these discontinuities should be maintained. Ridges and valleys are rounded off and little, but surface characteristic features might be wiped out or blurred and reduced, so that they can not be detected by the feature extraction algo-

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rithm. All linear filters show the trade-off between noise removal and information preservation.

In order to overcome these drawbacks, we propose to use an algorithm for parameterfree information-preserving surface restoration. The basic idea is to extract the data's signal and noise properties from the observed data and use this information for the filtering of the data. The extraction of these properties is based on generic a priori knowledge about the surface. This a priori knowledge also puts constraints on the data and is used for the regularization via the stabilizing function. For this stabilizing function smoothness constraints are used. The smoothness constraints used here are the principal curvatures, whose expectations are assumed to be zero. If the data does not correspond to the a priori knowledge or the model, the influence of regularization is weakened. Therefore discontinuities in the data are maintained. The signal and noise properties are extracted by simultaneously estimating the variance of the smoothness and the noise.

In this contribution we also examine the influence of pre-processing on feature extraction for DEMs. For this purpose classical filter techniques and the information-preserving filter are applied for pre-processing and compared with respect to noise reduction and the ability of preserving morphology. The resulting data sets are the inputs for a feature extraction algorithm extracting structure lines. The results of feature extraction are then evaluated with respect to the previous filtering and compared qualitatively and quantitatively.

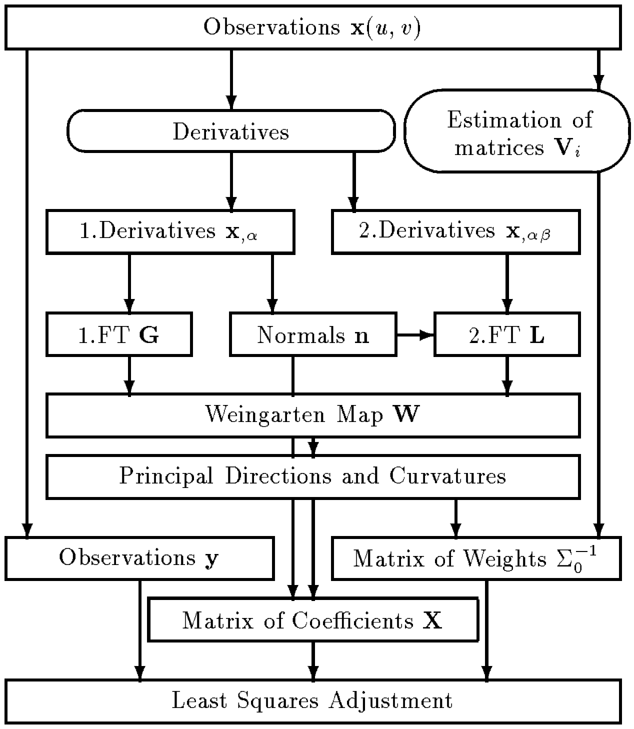
The paper is organized as follows: In section a brief description of the parameterfree information-preserving surface restoration's principle is given. Section gives an overview of the applied algorithm for feature extraction, followed by an introduction of possible evaluation criteria in section . In section 4.1.2 the results, including a comparision and evaluation of the pre-processing algorithms' influences, are given.

2 PARAMETERFREE INFORMATION-PRESERVING SURFACE RESTORATION

The parameterfree information-preserving surface restoration (PIPS) is designed for 3D surfaces in grid format $(\mathbf{x}(u,v),\ \mathbf{y}(u,v),\ \mathbf{z}(u,v))^T$, where u, v denote the surface coordinates which are used to represent the topology of the surface points. The principle of the algorithm is to estimate the signal and noise properties via variance component estimation (c. f. Förstner 1985) and use this information for filtering (c. f. Figure 1).

The algorithm is based on a geometric model. It is assumed that the expectations of the principal curvatures are zero, i. e. the surface can be locally approximated using planes. If the principal directions and the surface normals are known for the 3D representation, the principal curvatures can be computed by convolution.

The information about the surface's curvature properties is fully contained in the Weingarten map or shape operator $\mathbf{W}$ (Klingenberg 1973, Besl and Jain 1986). The eigenvalues of the squared Weingarten map $\mathbf{W}^2 = \mathbf{W}\,\mathbf{W}$ are the squared eigenvalues of $\mathbf{W}$. The eigenvectors of $\mathbf{W}^2$ are equal to those of $\mathbf{W}$ (c. f. Weidner 1993a). We use the



FT : Fundamental Tensor $\qquad \alpha,\ \beta \in [u,\ v]$

Figure 1: Flow Chart PIPS (3D)

eigenvalues for estimating the local variance of the surface's curvature.

The algorithm is based on the assumptions that

$$\mathbf{d} = \begin{pmatrix} \mathbf{d}_1^T & \mathbf{d}_2^T & \mathbf{d}_3^T \end{pmatrix}^T = \mathbf{u} + \mathbf{n}, \qquad (1)$$
$$E(\mathbf{d}) = \mathbf{u} \quad \text{and} \quad D(\mathbf{d}) = \sigma_d^2\,\mathbf{I}$$

with

$$\mathbf{d}_1 = \mathbf{x}(u,v) \quad \mathbf{d}_2 = \mathbf{y}(u,v) \quad \mathbf{d}_3 = \mathbf{z}(u,v)$$
$$E(\mathbf{k}_1) = \mathbf{0} \quad D(\mathbf{k}_1) = Diag(\sigma_{k1i}^2)$$
$$E(\mathbf{k}_2) = \mathbf{0} \quad D(\mathbf{k}_2) = Diag(\sigma_{k2i}^2)$$

where $Diag(p_i)$ denotes a diagonal matrix with entries p_i and $\mathbf{n} \sim N(\mathbf{0}, \sigma_n^2\mathbf{I})$. Other noise models, e. g. signal dependent noise, can easily be integrated.

If the surface normal and the principal directions are given, the following linear model with $m = 5$ groups of observations results (c. f. Koch 1988, p. 264):

$$E(\mathbf{y}) = \mathbf{X}\,\mathbf{u} \quad D(\mathbf{y}) = \sum_{i=1}^{5} \mathbf{V}_i\,\sigma_i^2 \qquad (2)$$

with

$$\mathbf{X} = \begin{pmatrix} \mathbf{X}_x^T & \mathbf{X}_y^T & \mathbf{X}_z^T & \mathbf{X}_{k1}^T & \mathbf{X}_{k2}^T \end{pmatrix}^T$$
$$\mathbf{y} = \begin{pmatrix} \mathbf{d}_1^T & \dots & \mathbf{d}_5^T \end{pmatrix}^T \quad \mathbf{d}_4 = \mathbf{k}_1 \quad \mathbf{d}_5 = \mathbf{k}_2$$

The matrix of coefficients, which describes the linear relation between the observations and the unknown parameters $\mathbf{u}$, splits into five submatrices, where the matrices

$\mathbf{X}_x$, $\mathbf{X}_y$ and $\mathbf{X}_z$ are identity matrices and the rows of the matrices $\mathbf{X}_{k1}$ and $\mathbf{X}_{k2}$ contain the convolution kernels for the principal curvatures $\mathbf{k}_1$ and $\mathbf{k}_2$. The structure of $\mathbf{V}_i$, which represents the mutual weighing of the observations in each group, must be known in advance (c. f. Koch 1988). Assuming independence of the obsvervations and equal variances for the coordinates simplifies (2) to

$$E(\mathbf{y}) = \mathbf{X}\,\mathbf{u} \qquad (3)$$
$$D(\mathbf{y}) = \sigma_d^2 \mathbf{V}_d + \sigma_{k1}^2 \mathbf{V}_{k1} + \sigma_{k2}^2 \mathbf{V}_{k2}$$

with

$$\mathbf{V}_d = \sigma_d^2\,\mathbf{I} \quad \mathbf{V}_{k1} = Diag(\overline{\sigma}_{k1i}^2) \quad \mathbf{V}_{k2} = Diag(\overline{\sigma}_{k2i}^2)$$

where $\overline{\sigma}_k^2$ denote a local estimate of the curvatures' variances. Based on this, the unknown parameters $\mathbf{u}$, i. e. the coordinates, and the variances can be estimated using iterative estimation.

Details are given in Weidner 1993b and Weidner 1994, also including details about the algorithm for graph surfaces (2.5D) used here.

3 FEATURE EXTRACTION

A number of algorithms for feature extraction has been proposed during recent years. Some of these approaches are designed for triangulated 2.5D-surfaces (e. g. Douglas 1986, Chou 1992), others for raster DEMs. In the following we focus on raster based algorithms, which might be classified as follows:

1. The first group of algorithms is based on functions of surface derivatives, e. g. Laplace or functions of the first and second derivatives (c. f. Enomoto *et al.* 1982). The structure lines are computed by determining the zero–crossings of the relevant criterion function. These algorithms lead to closed surface curves.
2. The second group of algorithms is directly based on the surface derivatives, either the first or the second. The structure lines are computed by determining the derivatives followed by non–maximum suppression.
3. The algorithms of the third group are based on classification. In most cases the criteria for classification are the surface curvatures (c. f. Haralick *et al.* 1983). Some approaches include line tracking based on gradients (c. f. Bevacqua and Floris 1987).
4. The last group of algorithms is hydrologically motivated and the structure lines are determined by simulating the water drain (c. f. O'Callaghan and Mark 1984).

Based on these different basic principles, there are also approaches which use a multiresolution analysis (c. f. Gauch and Pizer 1993) and, as already mentioned above, some approaches include vectorization of the results (c. f. Seemuller 1989). Here we only take results in raster format into account in order to use classical statistic techniques for binary classified sets in our evaluation.

The structure lines extracted with the algorithms listed above are of course of different type and meaning. The approaches 3 and 4 are mostly designed for DEMs and their relevant structure lines, i. e. valley and ridge lines. We therefore use an algorithm belonging to the third group. The flow chart of this algorithm is shown for the case of valley lines in Figure 2. The first step is to derive three sets of classified points. These sets are

DPV classification based on the locally computed number of higher points (c. f. Rieger 1992)
VAL classification of valley points (c. f. Bevacqua and Floris 1987)
EXV classification based on the locally computed exposition's variance

The following steps are binary *AND* and *OR* operations, which deliver the valley lines *SLV*.

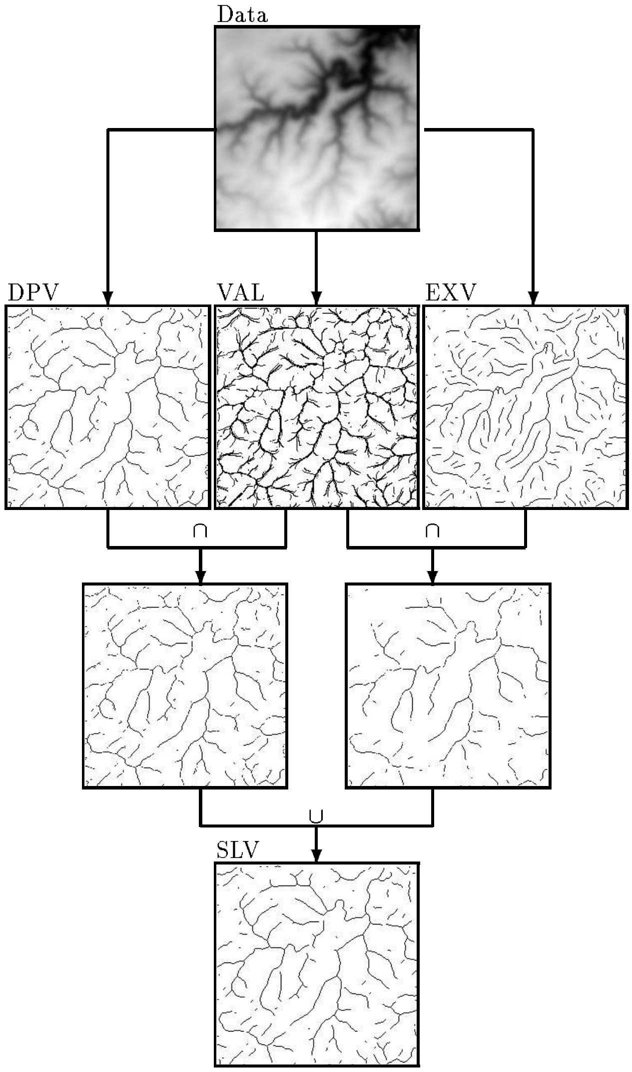


Figure 2: Structure Line Extraction: Flow Chart with Results for Linear Filtered Real Data Set (Rur)

4 EVALUATION CRITERIA

The advantage of the information-preserving approach in comparison to a linear filter is shown qualitatively in Figure 3. In homogeneous regions of both filtered data sets, noise has been reduced compared to the original data set. It is obvious that the linear filter smoothes all the data regardless of the structures which are contained in the data,

Figure 3: DEM Broeltal: Hill Shading a) Original b) Linear Filter c) Information-Preserving Filter

while the information-preserving algorithm maintains the structures. Although this example may give an initial hint to the performance of the algorithms, this is not satisfactory, because this hint is only based on visual inspection and includes no information about the influence of the pre-processing onto the following steps of data analysis. Therefore we are interested in numerical measures to evaluate the performance of the pre-processing algorithms discussed here.

A first approach to derive such numerical measures for the evaluation of filter techniques for digital images was described in Weidner 1991. The proposed quantities take the smoothing and the information-preserving properties into account. In Weidner 1994 improved quantities for this evaluation are given. The proposed measures are based on noise statistics and the maintenance of signal gradients, i. e. intensity step edges. This is appropriate for digital intensity images, because many feature extraction algorithms designed for those images are gradient based. For performance evaluation of pre-processing algorithms for DEMs, this seems not appropriate because a variety of feature extraction algorithms for DEMs are not based on gradients, but on the surface's curvature properties. Therefore we modify the proposed quantities with respect to the demands for DEMs. Furthermore we want to examine the influence of pre-processing by evaluating the discrepancies between the extracted binary structure line images quantitatively. The next two subsections deal with the numerical measures for our evaluation.

4.1 Quantities for Evaluation

In order to derive and compute qualitative measures for performance evaluation, the true surface and the true structure lines have to be known as reference. Therefore our test is based on the synthetic DEM given in Figure 4 and the related structure lines given in Figure 5. We distinguish between surface based quantities, i. e. quantities based on noise and signal properties of the filtered and the reference surface, and structure line based quantities, i. e. quantities which measure the discrepancy between binary structure line images. In the following we denote with

Figure 4: Test DEM (hill shaded)

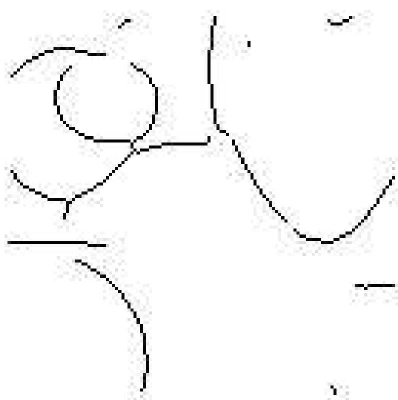


Figure 5: Structure Lines

$\mathcal{S}$	the set of surface points
$\mathcal{L}$	the set structure line (reference) points
$\hat{\mathcal{L}}$	a set of extracted structure line points
$\lvert\mathcal{L}\rvert$	the number of points of $\mathcal{L}$
$d(x,\mathcal{L})$	the shortest distance from point $x \in \mathcal{S}$ to $\mathcal{L} \subseteq \mathcal{S}$

4.1.1 Surface Based Quantities

Analogeous to the proposal in Weidner 1994, the surface $\mathcal{S}$ is segmented in two mutually exclusive regions (c. f. Figure 6)

$$\mathcal{S} = \mathcal{S}_{hom} + \mathcal{S}_{disc} \tag{4}$$

where $\mathcal{S}_{hom}$ denotes homogeneous regions (white) and $\mathcal{S}_{disc}$ non homogeneous or discontinuous regions (black). Based on this segmentation we propose two independent measures for evaluation:

- *property of smoothing*

$$PS = \frac{1}{\sigma_n^2(\mathbf{z})|\mathcal{S}_{hom}|} \sum_{\mathcal{S}_{hom}} (\hat{z}_i - z_{0i})^2 \tag{5}$$

where σ_n^2 is the noise variance of the input image $\mathbf{z}$ before filtering, which in case of synthetic data is known in advance, $\hat{\mathbf{z}}$ denotes the filtered data set and $\mathbf{z}_0$ the reference data set. In the optimal case, i. e. that noise is eliminated in homogeneous regions, $PS = 0$.

- *property of preserving information*

$$PP = \frac{1}{|\mathcal{S}_{disc}|} \sum_{\mathcal{S}_{disc}} \left(\mathrm{tr}\mathbf{H}^2(\hat{\mathbf{z}})_i - \mathrm{tr}\mathbf{H}^2(\mathbf{z}_0)_i\right) \tag{6}$$

with

$$\mathbf{H}^2 = \mathbf{H}\,\mathbf{H} \quad \text{and} \quad \mathbf{H}\text{: Hessian matrix}$$

The Hessian matrix $\mathbf{H}$ for 2.5D surfaces is approximately equivalent to the Weingarten map $\mathbf{W}$ of 3D surfaces and contains the information about the surface's curvature properties. $PP = 0$ in the optimal case.

Figure 6: Segmentation

4.1.2 Structure Line Based Quantities

Structure line extraction as carried out here is a binary classification. Therefore quantities which measure the frequency of incorrect pixel classification can be applied. We use

- Type I error rate (false positives)

$$\alpha(\hat{\mathcal{L}},\mathcal{L}) = \frac{|\hat{\mathcal{L}} \setminus \mathcal{L}|}{|\mathcal{S} \setminus \mathcal{L}|}, \quad \alpha \in [0,1] \tag{7}$$

- Type II error rate (false negatives)

$$\beta(\mathcal{L},\hat{\mathcal{L}}) = \frac{|\mathcal{L} \setminus \hat{\mathcal{L}}|}{|\mathcal{L}|}, \quad \beta \in [0,1] \tag{8}$$

- misclassification error for binary sets

$$\varepsilon(\mathcal{L},\hat{\mathcal{L}}) = \frac{|(\hat{\mathcal{L}} \setminus \mathcal{L}) \cup (\mathcal{L} \setminus \hat{\mathcal{L}})|}{|\mathcal{S}|} = (1-r)\,\alpha + r\,\beta, \tag{9}$$

$$r = \frac{|\mathcal{L}|}{|\mathcal{S}|}, \quad \varepsilon \in [0,1]$$

In the optimal case, the quantities are zero. Advantages and disadvantages of these quantities are e. g. given in Baddeley 1992. In order to overcome the drawbacks related to these measures, Baddeley 1992 proposed a metric to measure the discrepancy between two binary sets:

- Baddeley metric

$$\Delta_w^p(\mathcal{L},\hat{\mathcal{L}}) = \left[\frac{1}{|\mathcal{S}|}\sum_{x\in\mathcal{S}} |w(d(x,\mathcal{L})) - w(d(x,\hat{\mathcal{L}}))|^p\right]^{\frac{1}{p}} \tag{10}$$

with

$$w(x) = min(x,c) \quad \text{and} \quad c\text{: cutoff distance}$$

If there is no discrepancy between the binary sets, $\Delta = 0$. In our test we use $c = 5$ and $p = 2$.

5 RESULTS

In this section the results of our test and an evaluation are given. For the evaluation given in Weidner 1994, a variety of different filter algorithms has been included in the test. Here we restrict our test to a linear filter (binomial filter) and the information-preserving filter, because other known filter techniques for digital images are often based on an implicit or explicit piecewise constant signal model, which does not seem to be useful for DEMs.

The test is based on a synthetic data set, because knowledge about the true surface and structure lines as reference is needed for the quantitative evaluation. During the test, the reference surface and a noisy surface with additional uncorrelated noise $\mathbf{n} \sim N(\mathbf{0}, \sigma_n^2\mathbf{I})$ are used as input data for the filter algorithms. The filtered data sets are then used as input data for the structure line extraction algorithm. Based on the filtered data sets and the extracted structure lines, we apply the quantities given in

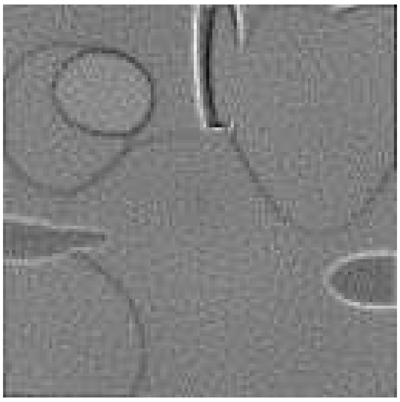


Figure 7: Difference image: noisy original - linear filtered data set (Binomial, 3x3, 3 Iterations)

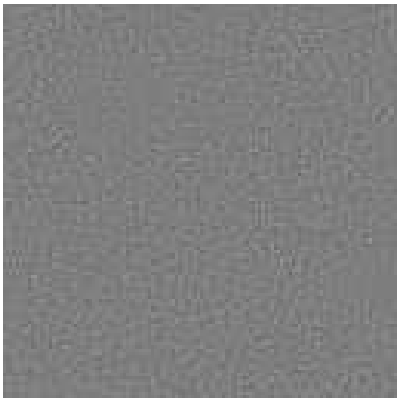


Figure 8: Difference image: noisy original - information-preserving filtered data set

section for the evaluation. Using the noiseless test data, we are interested in how a pre-processing algorithm handles a true/perfect data set. As there is no noise, the data set should not be changed by filtering. In case of the noisy test data set, we are interested in the degree of smoothing in homogeneous regions $\mathcal{S}_{hom}$ and the degree of information preserving, i. e. degree of reconstruction, in discontinuous regions $\mathcal{S}_{disc}$. During the tests, the tunable parameters related to the filter algorithms are not changed, otherwise the try-and-error-principle performed by an operator will almost always lead to satisfactory results. This mainly concerns the application of the linear filter, because the parameters needed for the information-preserving filter are estimated from the input data.

A first qualitative comparison is possible looking at the difference images between the noisy test data set and the linear and information-preserving filtered data sets given in Figure 7 and Figure 8. Both images are for sake of comparision spread with the same factor. If the performed filtering is optimal, there should be no structures visible in the difference images, but only white noise. In the difference images of the linear filtered data set, structures are obvious, but hardly any structures could be seen in the difference image of the information-preserving filtered data set.

In the following the results for the surface based quantities and the structure line based quantities are given and discussed. In the tables also the quantities for the noisy unfiltered test data set are included for comparision. We also include the results for varying number of iterations in order to discuss the influence of the tunable parameters width or number of iterations of the linear filter respectively. The linear filter's mask used here is 3×3.

Surface based quantities The results for the surface based quantities are given in Tab. 1. For the results of the filters with the noiseless surface as input, the quantity PS as given in (5) is not defined because $\sigma_n^2(\mathrm{z}) = 0$. In this case we modify PS to

$$PS^* = \frac{1}{|\mathcal{S}_{hom}|} \sum_{S_{hom}} (\hat{z}_i - z_{0i})^2$$

For the data set of the linear filtered noiseless surface the change of information is visible in both quantities PS^* and PP. The degree of change depends on the number of iterations or the size of the filter respectively as it was expected. The change of information is also obvious for the linear filtered noisy surface. The ranking of the results for PS is difficult, because not only the noise, but also the signal seems to be changed in homogeneous regions, otherwise PS should decrease and not increase.

$PS^* \approx 0$ indicates no significant change in homogeneous regions for the PIPS-filtered noiseless surface. This fact is proved by $PP = 0.12$. Applying PIPS for the noisy surface, the noise in homogeneous regions is significantly reduced ($PS = 0.14$), while at the same time the information is maintained. PIPS shows the lowest rate of change in information and reduces the influence of noise, which is obvious looking at the quantities PP for PIPS ($PP = 87.75$) and the unfiltered surface ($PP = 138.60$).

Filter		surface based quantities	
noiseless surface		PS^*	PP
Binomial, 3x3	1 Iteration	0.10	1269.60
	3 Itereations	0.48	1896.08
	10 Iterations	2.79	2335.06
PIPS		0.00	0.12
surface with $\sigma_n = 1$		PS	PP
unfiltered		1.00	138.60
Binomial, 3x3	1 Iteration	0.24	1295.73
	3 Iterations	0.53	1902.43
	10 Iterations	2.81	2336.29
PIPS		0.14	87.75

Table 1: Surface based quantities

These quantities are computed based on the segmentation shown in Figure 6. In order to evaluate the influence of the chosen segmentation on the quantities PS and PP, different segmentations with little disturbances have been used for their computation. Of course the quantities changed, but the ranking and the statements given above remain valid for these different segmentations. This also has been proved for robust estimations (Rousseeuw and Leroy 1987) of the quantities PS and PP, although the differences for the quantities are smaller.

Structure line based quantities The results for the structure line based quantities are given in Tab. 2 and Tab. 3. If the pre-processing for the structure line extraction algorithm is optimal, the structure line based quantities should be zero, or in the case of filtered noisy data at least significantly reduced compared to the result of the unfiltered noisy data set. The effects of noise are obvious for the unfiltered noisy data set. The noise leads to missing and spurious pixels in the structure line image (Figure 9), which leads to high quantities of α, β, ε and Δ.

Filter		α	β	ε
noiseless surface				
Binomial, 3x3	1 Iteration	0.006	0.387	0.016
	3 Iterations	0.011	0.586	0.025
	10 Iterations	0.009	0.749	0.028
PIPS		0.000	0.019	0.001
surface with $\sigma_n = 1$				
unfiltered		0.046	0.522	0.058
Binomial, 3x3	1 Iteration	0.012	0.425	0.022
	3 Iterations	0.012	0.616	0.027
	10 Iterations	0.009	0.757	0.028
PIPS		0.010	0.312	0.017

Table 2: Structure line based quantities: α, β, ε

Filter		Δ
noiseless surface		
Binomial, 3x3	1 Iteration	0.62034
	3 Iterations	0.70004
	10 Iterations	0.99957
PIPS		0.17969
surface with $\sigma_n = 1$		
unfiltered		1.79918
Binomial, 3x3	1 Iteration	0.77741
	3 Iterations	0.75442
	10 Iterations	0.99400
PIPS		0.77729

Table 3: Structure line based quantities: Δ

Linear filtering leads to smearing discontinuities in the noiseless and noisy filtered images. Therefore the rate β of false negatives pixels, i. e. pixels that are not classified as structure line points, although they belong to $\mathcal{L}$, increases as well as the misclassification error ε proportionally to the number of iterations or the width of the linear filter respectively. This also seems to be true for the Baddeley metric for the results of the noiseless surface, whereas in the noisy case, the Baddeley metric indicates the trade-off between smoothness of the data and information preservation. Nevertheless linear filtering improves the quantities compared to the unfiltered data set.

The structure line image of the PIPS-filtered noiseless surface (Figure 12) indicates no severe differences in topology, but some disturbances in localization. α is approximately 0, and the other quantities are the lowest compared to the linear filtered surface. The changes of localization are also obvious in the Baddeley metric, but Δ for PIPS is signifcantly lower as for the linear filter, because the linear filter does not only affect the localization, but also the topology, i. e. structure line information is missing.

In case of the noisy PIPS-filtered data set, visual inspection of the structure line images (Figure 13) also indicates changes of localization and some spurious pixels. In this area of the data set the filter is not able to seperate between noise and signal, because of the local SNR. Therefore the rate of smoothing is reduced. Nevertheless the rate α (false positives) is improved compared to the unfiltered data set, but is similar to the rates of the linear filter. The noisy PIPS-filtered data set also obtains better rates for β and ε as the unfiltered and linear filtered data

Figure 9: Structure lines, $\sigma_n = 1$, unfiltered

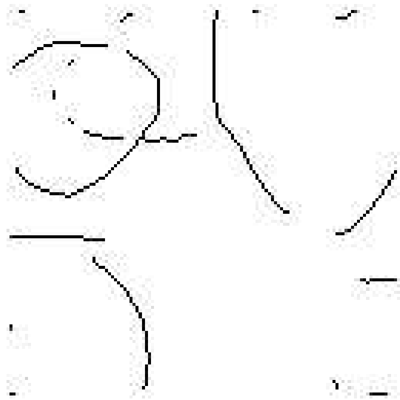


Figure 10: Structure lines, Binomial Filter, 1 Iteration

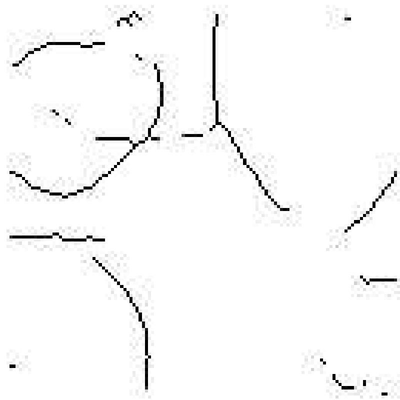


Figure 11: Structure lines, $\sigma_n = 1$, Binomial Filter, 3 Iterations

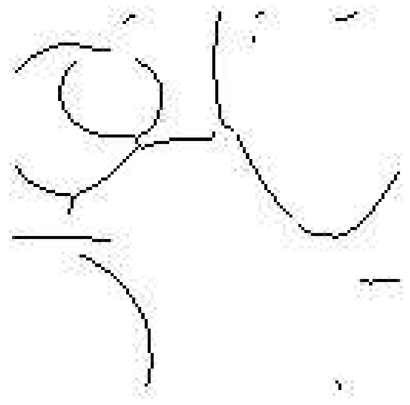


Figure 12: Structure lines, PIPS

Figure 13: Structure lines, $\sigma_n = 1$, PIPS

sets, but the Baddeley metric indicates no significant difference between linear and information-preserving filtered surfaces, although some structure lines are missing for the linear filtered set. The reason for this is the change of localization of structure lines, which differ at about 1 pixel compared to the reference structure lines (Figure 5).

6 CONCLUSION

In this contribution we discussed pre-processing of data in order to remove or at least reduce noise and its influence on feature extraction for DEMs. In many cases linear filters are used for pre-processing, although it is known that linear filtering does not only reduce noise, but may also lead to a loss of information. Furthermore, in many applications the tunable parameter of the filter has to be chosen by an operator based on his experience. In order to overcome these drawbacks, we proposed to use an algorithm for parameterfree information-peserving surface restoration (PIPS). The basic idea of this algorithm is to extract the data's noise and signal properties based on generic a priori knowledge and use this information for the filtering of the data. We applied both filters to synthetic test data and evaluated the results of pre-processing quantitatively based on surface and structure line based quantities. The quantities indicate some advantages for the PIPS-algorithm, although in some cases the results were almost comparable. The influence of the tunable parameter of the linear filter is obvious. Therefore our proposed algorithm has the advantage, that no parameter has to be fixed by an operator. The results are better or at least as good as the results of the linear filter. Futher examinations will be made on other appropriate test data sets with more structure line information. Furthermore tests will be made for other feature extraction algorithms for DEMs and digital intensity images.

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