RECONSTRUCTION OF BAD VALUES IN OPTICAL MEASURED SURFACE DATA

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Abstract :

Optical measured data sets contain a number of "bad values". Many filters and attached processing steps, needed a complete grid of data points.

Therefore traditional reconstruction techniques often use simple polynomial or spline interpolation respectively approximation algorithms. This causes problems like overshooting and a strong dependence from the neighbour given data points. These neighbour data points are often affected by artifacts because of optical measurements. This result in an unfavourable surface reconstruction.

The goal is to minimise the effects caused by artifacts and to get reconstruction results, which correspond better with original surfaces.

Using á priori knowledge about reliability of the measured data points leads to weights for every single given data point. With this a minimisation of the influence of the optical artefacts is possible.

Key words: bad value, surface reconstruction, confocal microscope, white light interferometer

1 Introduction

Modern technical surfaces and materials like AlSi or laser texture surfaces have structure elements in the micro- or nanometer range. Traditional tactile methods distort with their morphological filter effects these structure elements. Traditional tactile methods in the roughness measurement are also very time consumption. Optical measurement techniques can make a substantial progress in this field.
Using white light interferometers or confocal microscopes leads to other kind of problems. For individual measurement points the information content collected during the measurement isn't always sufficient to calculate a secure value. These points arecalled "bad values". The measurement systems doesn't attached them with a metrology value. Beside this "bad values" a couple of additional effects appear in measurement results. Confocal microscopes and white light interferometers often show overshooting in their data sets near sharp edges. This overshooting is also called „bat-wings".
Many traditional reconstruction methods use simple polynomial or spline interpolation. These techniques are strongly depending from the neighbouring given data points. Unfortunately the neighbouring given data points are often "bat-wings" and the reconstruction techniques shouldn't be affected by optical artifacts.
Using weights for every single given data point could minimise influences of optical artifacts. Weights shall be generated not only from topography data but also from furthermore measurement information like image stacks by confocal microscopes and á priori knowledge.

2 Algorithmic

Many interpolation methods need a equidistant grid like most of the FFT-methods. The CCD-Chip or CMOS-Chip in the optical measurement systems provides equidistant grids. These grids normally have holes in various sizes because of the "bad values". So a method is needed which could uses irregularly spaced data points.

2.1 Shepard Interpolation

Shepard [1] introduced a method for irregularly spaced data points (see also [2-7]). Eq. 1 shows the Shepard interpolation for a whole surface, with a weight function w_j for all N nodes (x_j, y_j) and a corresponding function f_j respectively given data points (excluding the "bad values"):

$$\phi(x,y) = \sum_{j=1}^{N} w_j(x,y) f_j \quad . \qquad (1)$$

The normal weight function for a single supporting point (x_j, y_j) is given as:

$$w_j(x,y) = \frac{r_j(x,y)}{\sum_{i=1}^{N} r_i(x,y)} \quad . \qquad (2)$$

The distant function $r_j(x,y)$ is defined as:

$$r_j(x,y) = \frac{1}{\left(\sqrt{(x-x_j)^2 + (y-y_j)^2}\right)^{\mu}} \quad , r_j(x,y) = \begin{cases} \geq & 0 \quad \text{for all } (x,y) \\ = & 1 \quad \text{for all } (x,y) = (x_j, y_j) \\ = & 0 \quad \text{for all } (x,y) = (x_k, y_k), k \neq j \end{cases} \qquad (3)$$

In this case μ is a smoothing factor and should be in **the range of** $0 < \mu < \infty$. **The best results** are normally at $\mu = 2$. Besides this there are a couple of more definitions for distant weight functions (for example in [8]).

The improvement is to create new weights which use á priori knowledge about the given data points. Using a general weight function $g(x_j, y_j)$ modifies the Shepard's interpolation equation to the following:

$$\phi(x,y) = \frac{\sum_{j=1}^{N} r_j(x,y)\; g(x_j, y_j)\; f_j}{\sum_{i=1}^{N} r_i(x,y)\; g(x_i, y_i)} \qquad (4)$$

Using Information from the whole measurement data set could lead to an individual "mutual trust map" for every single measurement. The "mutual trust map" should only based on the measurement data set, preliminary ideas of the measurement processes and á priori knowledge of the surface.

In the following subsection different weight functions are discussed.

2.1.1 Weights derived by a moving average/median

"Bat-wings" is a common phenomenon, it's a good choice to use a weight which minimise it's influence on reconstruction results. One characteristic of "bat-wings" are that their values normally are not similar to the local average of the surrounding surface. To achieve this, a square shape is moving about the surfaces and every value of the given data point inside this shape, is taken to build their mean or to find their median. M is the number of given data points inside a square shape (see also figure 1). Building the square of the residual between the local mean or local median and the surface data f_j. Normalisation of the weights in a range from 0 for a bad and 1 for a good reliability results in following equations:

$$g(x_j, y_j) = \frac{1}{\left(f_j - \frac{1}{M}\sum_{k=1}^{M} f_k\right)^2 + 1} \tag{5}$$

$$g(x_j, y_j) = \frac{1}{\left(f_j - \underset{M}{\text{median}}\, f_k\right)^2 + 1} \tag{6}$$

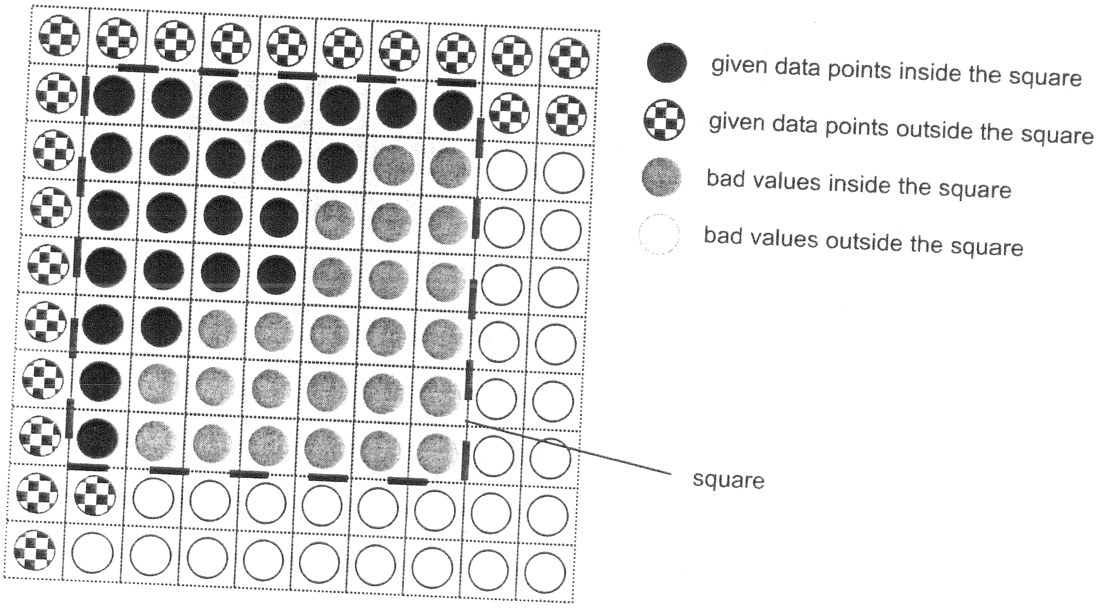

Fig. 1: *bad values and given data points distribution in-, and outside of the square of interest (here M=24)*

For better results M should greater than 5. Over this the edge length of the size of the square should be at least 7x7 pixel or higher.

2.1.2 Weights derived by the gradient of the surface

An additional way to detect "bat-wings" is, to take gradients of given data points as decision criterions:

$$g(x_j, y_j) = \frac{1}{1 + \left|\frac{\partial^2}{\partial x \partial y} f_j\right|}. \tag{7}$$

Usage of reasonable thresholds could improve the success of slant weights. Because of physical limitations measuring instruments can detect data up to a certain slope angle. A higher slope represents insecure values and their weight should be set to zero.

2.1.3 Weights derived from intensities

Many optical measurement systems provide not only metrology data but also data about intensity during the measurement. The intensity normally various within different surface areas, this depends on different material properties, current surface slopes and steep edges. In general because of the better signal-to-noise-ratio at high level intensities these values are more secure.

Using the maximum intensity $I_{\max}$ leads direct to the Intensity weights:

$$g(x_j, y_j) = I_{\max}(x_j, y_j) \tag{8}$$

A threshold in the dimension of the noise is recommended for those weights.

2.1.4 Weights derived from the intensity figures

Confocal microscopes use image stacks for every measuring step to calculate the height value z. These intensity figures could also be used to calculate the reliability of the measurement results. Ideal intensity figures are normally symmetric. Non optimal measuring conditions appear as unsymmetrical intensity figures, which can be characterized using the skewness known as the 3rd moment.

For better results the intensity figure $I(z)$ is limited by a threshold operator. The corresponding height values are z_1 and z_2 with $z_1 < z_2$. The intensity density underlying is:

$$h_I(z) = \begin{cases} \dfrac{I(z)}{\int_{z_1}^{z_2} I(z)\,dz} & z_1 \le z \le z_2 \\ 0 & \text{otherwise} \end{cases}, \qquad (9)$$

with mean

$$\bar{I} = \int_{z_1}^{z_2} z\, h_I(z)\,dz \qquad (10)$$

and variance

$$\sigma_I^2 = \int_{z_1}^{z_2} \left(z - \bar{I}\right)^2 h_I(z)\,dz \quad .(11)$$

The skewness of the intensity figure is defined as:

$$S_j = \frac{1}{\sigma_I^3} \int_{z_1}^{z_2} \left(z - \bar{I}\right)^3 h_I(z)dz \quad , \qquad (12)$$

which results in the following weight:

$$g(x_j, y_j) = \frac{1}{1 + |S_j|} \qquad (13)$$

3 Example

The following example shows the influence of the mean weight on the Shepard interpolation. Figure 2 shows an AlSi surface with a couple of particles. The figure is grey coded lower values are darker, "bad values" appear as holes. Near to "bad values" are a lot of "bat-wings".

This data set is reconstructed with the normal Shepard interpolation (Eq.1-3) figure 3. Clearly to see is that the normal Shepard interpolation depends strongly on the "bat-wings". To minimise this effect mean weights are used, see subsection 2.1.1.

Figure 4 shows the same reconstructed surface. Here the mean weights are grey coded. Low weights are dark and high weights are light. The image shows a good consent between the "bat-wings" and the low weights.

Figure 5 shows the result of the Shepard interpolation with the mean weights. The influence of the overshooting is strongly reduced. The reduction is near the "bat-wings" larger than farer away. To compare both methods figure 6 shows the difference between the "normal" and the modified Shepard interpolation". Using the other weights the behaviour is quite similar.

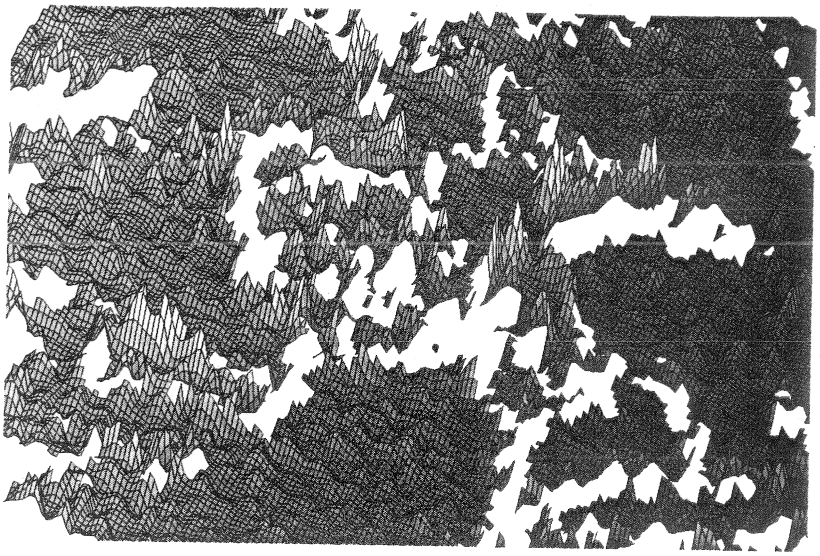

Fig. 2: AlSi Surface with "bad values" and "bat-wings"

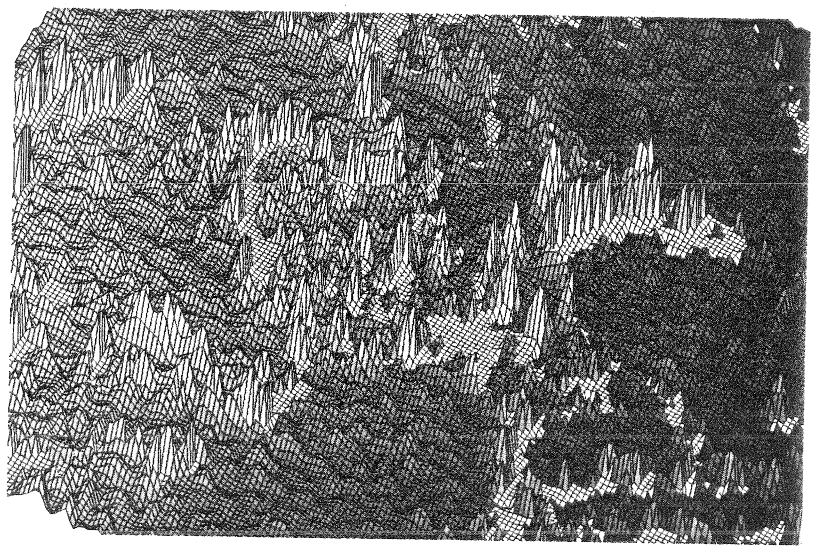

Fig. 3: AlSi Surface reconstructed with Shepard

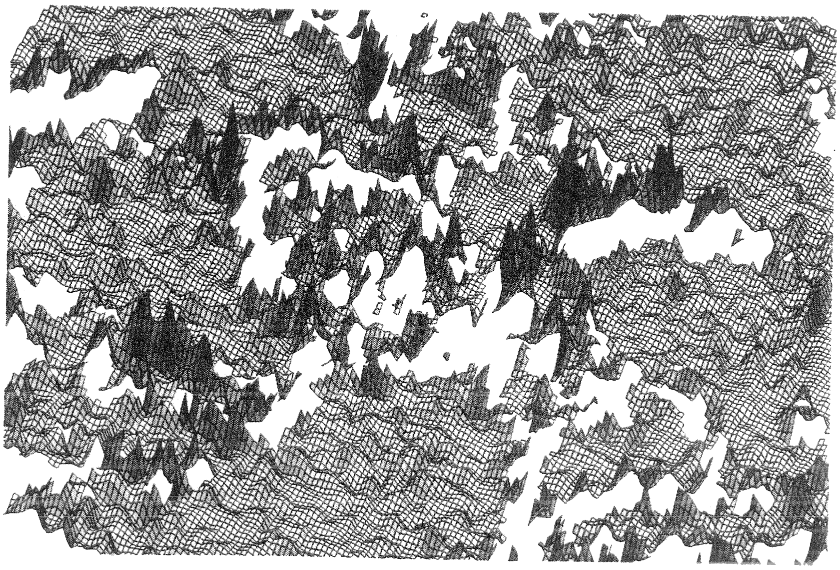

Fig. 4: AlSi surface with grey coded mean weights

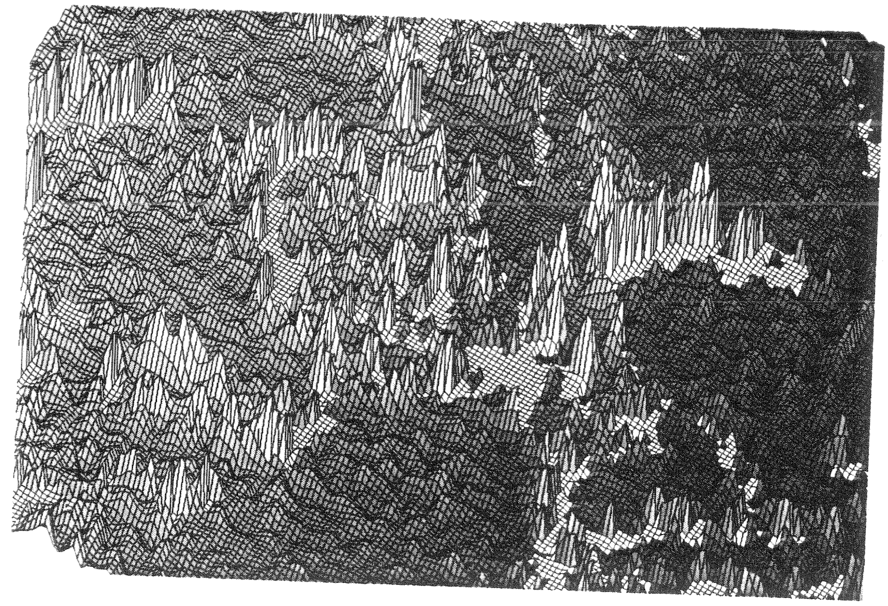

Fig. 5 Shepard interpolation with the mean weights

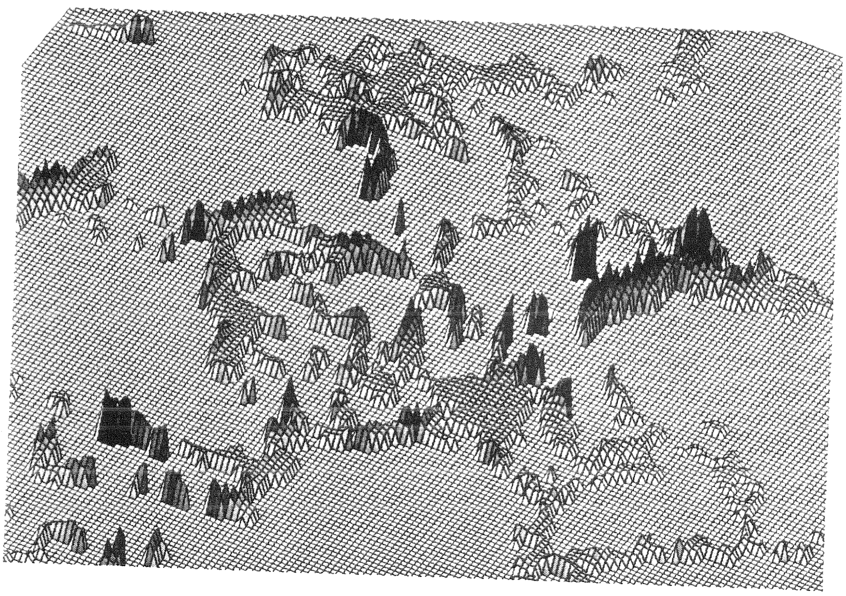

Fig. 6: Difference between normal Shepard interpolation & Shepard interpolation with mean weights

4. Conclusion

The foregoing weights for the Shepard interpolation enables us to improve reconstruction results for optical measurement systems. The weights are especially designed to react on some of the common problems like "bat-wings" in optical measured data sets. Over this it's also possible to use this weights as an indicator for "bat-wings" and other optical artifacts. Using these weights as an indicator, these values could be exclude from given data points. That makes these points to second order "bad values", which also could be reconstructed by the introduced way.

Besides the standard usage of Shepard interpolation and the new introduced weights it is also possible to combine different weights for even more improved reconstruction results. If the surfaces properties are well known, special designed weights could be used, which compare the measured surface data with the expected results.

5 References

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