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Robust surface fitting—Using weights based on à priori knowledge about the measurement process

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ABSTRACT

Modern surface layouts like automotive cylinder liners, turbine blades or seal faces need high information content. This high information content can only be reached with modern 3D-surface measurement techniques like confocal microscopy or white light interferometry.

For an analysis of the surface properties, an antecedent surface fitting is necessary. This surface fit has to be robust and must be based on trustworthy data.

According to the optical measurement techniques there are many known effects, which lead to wrong or insecure measuring data. Using à priori knowledge about the measurement process leads to knowledge about surface structures, which otherwise tend to be unsure or wrong. Examples for the confocal microscopy are "bat-wings" at sharp edges, multiple peaks because of oil films or surface coating. White light interferometry also has problems with speckles, when the surface structures have the size close to the interference length of the white light interferometer.

Using this knowledgebase for a pre-analysis of the surface data, a confidence level for every single data point could be calculated. That leads to a weighting function, which is usable with the commonly known surface fitting methods.

In this work different weighting methods are introduced. Some weighting methods are based on the original measured data and the à priori knowledge about the measurement method. Other weighting methods also use information about the measurement process, for example, the sharpness and skewness of a confocal peak or the signal to noise ratio. The weights could also be based on à priori knowledge about the surface and the structures on the surface, for example, sharp edges or surface areas with bad reflectivity properties.

There are combinations with each other, as well as with the already known weights from the common surface fitting methods from the regression analysis. This leads to a regression analysis which based on measured data with a higher reliability. The reducting of the measurement device influence provides a better comparability of surface data.

1. Introduction

Modern technical surfaces like automotive cylinder liners, turbine blades, seal faces, and laser-textured surfaces have structure elements in the micro- or nanometer range. They have high information content, which can only be achieved using modern 3D-surface measurement techniques like confocal microscopy or white light interferometry. Furthermore, traditional tactile methods also distort the structure elements due to their morphological filter effects. They are also very time consuming. For these reasons optical measurement techniques can make a substantial progress in this field.

2. Uncertain measurement results

The optical measurement techniques come along with a couple of effects appearing in the measurement results. Another problem are multiple reflexions caused by oil films or surface coatings. They can also appear at step edges, when light above and beneath the edge is reflected. White light interferometry also has problems with speckles and "bat-wings" [1,2], when the surface structures have a size close to the coherence length of the white light interferometer. Also confocal microscopes sometimes show overshooting in their data sets near sharp edges.

One problem appears mainly in confocal microscopy: the limitation of the intensity range of the light sensor. The light sensor is normally a CCD-array and can only detect light within a certain intensity range. Technical surfaces often have high-reflective and low-reflective areas in the same region of the surface depending

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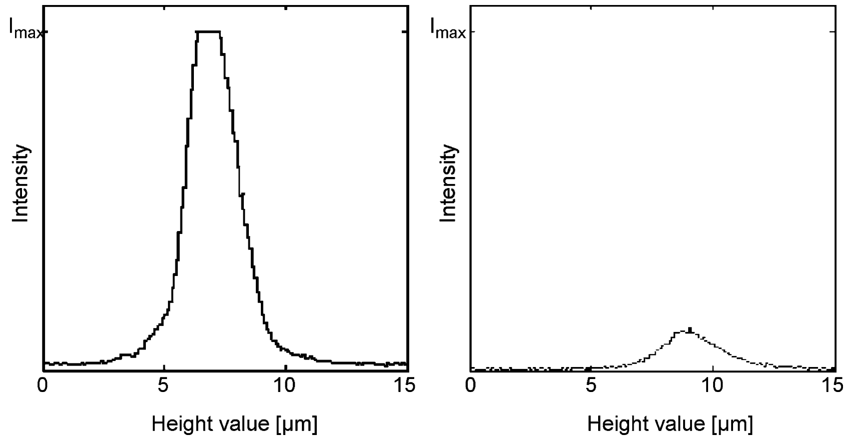

Fig. 1. An overexposed confocal curve (left) and an underexposed confocal curve (right) measured at the same surface.

on different material properties, surface slopes and steep edges. The problem is that it is not possible to measure the whole surface with an adequate amount of light. Fig. 1 shows two confocal curves measured at the same surface: an overexposed one (left) and an underexposed one (right). In the overexposed confocal curve, the position of the maximum intensity is marked with a vertical line. This shows the asymmetrical curve progression of the confocal curve. Theoretical research shows also a asymmetrical curve progression [3,4]. The evaluation of this confocal curve with a center-of-mass algorithm leads to an offset in the resulting height value. Since the offset depends on the size of the overexposure and the overexposure is not constant, the height values are inaccurate. On the other hand, the underexposed curve has a high signal-to-noise ratio and hence the measurement uncertainty is increased.

3. Surface fitting

A common surface fitting method is the least square analysis. The big advantage using least square in combination with a linear model function is a fast and explicit solution, because of the affiliation to a system of linear equations. There is also the possibility to define weights for every single data point. In Eq. (1) a weighted least square estimator is shown [5]:

$$\hat{s} = \mathbf{X}(\mathbf{X}^{\mathrm{T}}\mathbf{W}\mathbf{X})^{-\mathbf{1}}\mathbf{X}^{\mathrm{T}}\mathbf{W}\vec{h}, \tag{1}$$

with the data matrix $\mathbf{X}$, the height values $\vec{h}$ and the weighting matrix:

$$\mathbf{W} = \begin{pmatrix} w_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_n \end{pmatrix}, \quad w_n > 0, \ \ i = 1, \ldots, n, \tag{2}$$

where $w_i(x, y)$ are the weights for all n data points in the x,y-plane. Different weighting strategies can be used simultaneously:

$$w_i(x, y) = w_{i,\mathrm{rob}}(x, y) w_{i,\mathrm{conf}}(x, y). \tag{3}$$

The weighting function $w_{\mathrm{rob}}(x, y)$ is used for a robust fitting of the reference plane and $w_{\mathrm{conf}}(x, y)$ represents the confidence level of the data points. The definition of the confidence weight is described in the following section. Different confidence weights could also used simultaneously as described in (3).

4. Different weight functions

4.1. Weights derived by a moving average/median

"Bat-wings" is a common phenomenon; it is a good choice to use a weight, which minimises the influence on the reference plane. One characteristic of "bat-wings" is that their height values are normally not similar to the local average of the surrounding surface. To apply this, a local average or median is used to generate the weights. The local average should only be based on given data points and should reconstruct data points also called "bad values". The number of points used in this case is m. For the weights, the square of the residual between the local mean or local median and the surface data f_j is calculated. Normalisation of the weights in a range from 0 for a low and 1 for a high reliability results in following equations:

$$w_i(x, y) = \frac{1}{\left(f_i - (1/m)\sum_{1=k}^{m} f_k\right)^2 + 1}, \tag{4}$$

$$w_i(x, y) = \frac{1}{\left(f_i - \mathrm{median}\, f_k\right)^2 + 1}. \tag{5}$$

4.2. Weights derived by the gradient of the surface

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

$$w(x, y) = 1 \frac{1}{1 + |(\partial^2/\partial x \partial y) f_i|}. \tag{6}$$

Usage of reasonable thresholds can improve the success of slant weights. Because of physical limitations, measuring instruments can detect data up to a certain slope angle, normally defined by the measurement instruments manufactures since higher slopes represent more unsecure values, their weight should be set to zero.

4.3. Weights derived from intensities

Many optical measurement systems not only provide metrological data but also data about the intensity. The intensity normally varies within different surface areas. In Section 2 it was shown that because of the lower signal-to-noise-ratio at high-level intensities these values are more secure. This leads to the following weights:

$$w_{i,\mathrm{int}\ 1}(x, y) = \frac{I_i(x, y)}{I_{\max}}. \tag{7}$$

The maximum detectable intensity of the CCD-array is given by I_{max} and $I_i(x,y)$ is the intensity for a single data point. The problem of overexposed confocal curves was introduced in Section 2. Overexposed confocal curves leads to wrong height values, so they should not used at all. This leads to an additional binary weight:

$$w_{i,\text{int }2}(x,y) = \begin{cases} 0 & I_i(x,y) \geq I_{max} \\ 1 & I_i(x,y) < I_{max} \end{cases}. \quad (8)$$

These weights result in the intensity weight function:

$$w_{i,\text{int}}(x,y) = w_{i,\text{int }1}(x,y)\, w_{i,\text{int}2}(x,y). \quad (9)$$

Confocal microscopes use image stacks for every measuring step to calculate the height value z. These confocal curves can 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 the derivation of skewness of the intensity figure see Appendix A. The weight is defined as follows.

4.4. Weights derived from the confocal curves

$$w_i(x,y) = \frac{1}{1+|S_i|}. \quad (10)$$

It has been pointed out that the confocal curves, especially when using objectives with high numerical aperture, have asymmetrical and skewed confocal curves. Therefore, the reference skewness S_{ref} must be defined in advance. In order to determine the reference skewness a foregoing measurement with a plane mirror has to take place. This results in the following weight:

$$w_i(x,y) = \frac{1}{1+|S_i - S_{ref}|}. \quad (11)$$

4.5. Weights derived from the intensity ratio of confocal curves

The occurrence of multiple peaks in the confocal curve was discussed in Section 2. Good algorithms can deal with the problem that they do not average over different peaks. However, multiple peaks indicate that the measuring process may lead to inaccurate results. The ratio between the cumulative intensity of the light within the FWHM $\sum_{FWHM} I_i(z)$ (full-width-at-half-minimum of the confocal curve i) and the accumulated intensity of the measuring process $\sum_{\in z} I_i(z)$ is

$$w_i(x,y) = \frac{\sum_{FWHM} I_i(z)}{\sum_{\in z} I_i(z)}. \quad (12)$$

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Appendix A

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

$$h_I(z) = \frac{I(z)}{\int_{z_1}^{z_2} I(z)\, dz}, \quad z_1 < z < z_2, \quad (13)$$

with mean

$$\bar{I} = \int_{z_1}^{z_2} z\, h_I(z)\, dz, \quad (14)$$

and variance

$$\sigma_I^2 = \int_{z_1}^{z_2} (z-\bar{I})^2 h_I(z)\, dz. \quad (15)$$

The skewness of the intensity figure is defined as

$$S_i = \frac{1}{\sigma_I^3} \int_{z}^{z_2} (z-\bar{I})^3 h_I(z)\, dz \quad (16)$$

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