Abstract—To be introduced a non-iterative robust-
Gaussian filter-operator for surface roughness parameters. 
We use modified bilateral filtering method with an initial 
approximation for the roughness measurement. The operator is robust and fast in the sense that it can suppress 
outliers in a non-iterative way. The results are compared 
with the Gaussian regression filtering method.

I. INTRODUCTION

Characterizing technical surfaces is important with 
respect to their frictional behavior, with respect to their 
coatability or other properties [1]. Surfaces may have 
deep pores or grooves which need to be added to the 
roughness and may not at all shift the waviness profile. In 
nanotechnology as well friction is an important item to 
consider roughness, furthermore the uncertainty of 
critical dimension measurements. Here singular particles, 
e.g. due to contamination, may bias the estimates of the 
waviness profile [2].

Filtering surface profiles with outliers is a challenging 
task in the surface engineering, if the algorithm is used 
for real time computing. The outliers are mostly artifacts 
or noises with much larger or much smaller values than 
their neighbors. Industrial usage in automation 
technology demands for robust filtering to detrend 
waviness and roughness to characterize a surface. In 
particular automotive and aviation technology but also 
nanotechnology is confronted with surfaces with singular 
grooves or spikes. Gaussian maximum likelihood 
statistics presumes normally distributed residuals. In 
rroughness analysis, the waviness profile is defined as 
estimate of a low pass filter and the roughness as its 
residuals. In presence of deep pores, grooves or spikes the 
requirement of normally distributed roughness values is 
no longer valid such that robust statistics is employed [3].

Literature offers a variety of robust M-estimators to treat 
such surface filtering accordingly. Usually M-estimators 
work iteratively. Their computing performance in speed 
and efficiency as well as their robustness (break down 
point) vary so that we have investigated a method that 
works non-iteratively [4].

It is appropriate to eliminate them, while keeping the 
rroughness profile intact. Maximum likelihood (ML) 
estimators which are obtained by minimizing the sum of 
the squares of the residuals garble the profiles with 
outliers. Commonly used ML-estimator are the Gaussian 
filter [1], which even has been standardized (ISO 16610-
21/28), and the Spline filter [4], on which a proposed 
standard has been published (ISO/TS 16610-22) [5].

Robust statistics proposes M-estimators that may 
operate iteratively. They may at first determine a biased 
estimate obtained from ML-estimation delivering 
residuals that are input parameters to a weighting 
function whose argument decreases the more the residual 
increases. Some even propose cut values truncating 
residuals that exceed a given value. Such a cut value 
using truncating weighting function would be the step 
function and the estimation procedure is referred to as 
least trimmed squares. A modified version of a least 
trimmed square estimation has been standardized in ISO 
13565 [6] called a “quasi-robust” two-stage filter. It is a 
filtering method to be applied to technical surfaces with 
pores and grooves using the positive residuals and 
rejecting all negative residuals. In the first stage a 
Gaussian low-pass filter (GLPF) is applied. To select 
only positive residuals, the primary profile points below 
the waviness points (the so-called mean line) are replaced 
by the mean line itself. Finally, a second filtering step is 
performed by applying the GLPF to the modified profile. 
Brinkmann et al. [7] demonstrated an iterative regression 
technique, which applies a GLPF few times suspending 
on the profile values and the location of the weighting 
function of the profile. Another commonly used robust 
M-estimator, which is independent of whether the outlier 
is positive or negative, but which still uses a cut value is 
defined by the Tukey objective function [8].

Our paper is based on the works of McCool [9] and 
Tomasi et al. [10]. The authors suggested diffusion 
filtering (DF) and bilateral filtering (BF) to smooth 
images. The DF algorithm equalizes iteratively extended 
regions by estimating partial differential equations. A BF 
is a non-iterative noise separating filter. The value f(x) at 
point x is replaced by a weighted mean of measured 
values from adjacent points. The weights are Gaussians 
and depend not only on the length but also on the 
differences in the values. Consequently, bilateral filter 
could be realized by two kernels: the outlier, and the field 
kernels.

In this contribution, we use modified bilateral filtering 
(MBF) for roughness profiles with an initial
approximation procedure to suppress outliers. In the following chapter we formalize the notion of the MBF operator and in section 3 we show experiments for the PTB roughness standard profile.

II. Method

The bilateral filtering is based on the following equation [6]:

$$h(x) = k^{-1}(x) \int f(\xi) c(\xi, x) b((f(\xi), f(x)) \xi d\xi$$

$$= \int \int f(\xi) c(\xi, x) b((f(\xi), f(x)) \xi d\xi$$

where $h(x)$ is the normalized gauge of the profile, $k^{-1}(x)$ is a normalization function, $f(x)$ is the measured profile value at x, and $f(\xi)$ is the profile value at $\xi$. $c(\xi, x)$ is the outlier-, and $s((f(\xi), f(x)))$ is the field filter kernels, which are Gaussians, accordingly:

$$c(\xi, x) = \frac{1}{\lambda \alpha} \exp \left[-\pi \frac{(x-x_0)^2}{\lambda \alpha}\right]$$

$$\alpha = \frac{\log 2}{\pi} = 0.4697 \ [4].$$

$c(\xi, x)$ moderates the geometric analogy between the neighborhood center $x$ and a nearby profile value $\xi$, while $s((f(\xi), f(x)))$ applies the similarity between the $x$ and $\xi$. The value at $x$ is substituted by a mean of comparable and adjacent values. In smoothed profile sections, values in a narrow-minded neighborhood are similar to each other, and the approximation $k^{-1}(x)$ is close to one. The BF works as a domain filter, and discards the poorly correlated differences between surface values caused by noise, but is not able to remove the outliers. This is on account of the initial gauge $f(x)$ in $s((f(\xi), f(x)))$ is meaningful different from its precise value, and small improvement comes to $h(x)$ from such neighbors due to the infinitesimal weights reversed by the range function. Thus, the outliers stand nearly unvaried neighbors due to the infinitesimal weights reversed by the range function. Therefore, we suggest the MBF algorithm to use initial estimator $m(x)$ while replace $f(x)$ in Eq (2):

$$e(x) = \frac{\int f(\xi) c(\xi, x) b((f(\xi), m(x)) \xi d\xi}{\int c(\xi, x) b((f(\xi), m(x)) \xi d\xi}$$

The estimator $m(x)$, around point $x$

To achieve the MBF algorithm first

i) initial estimation by $m(x)$, for each measured profile value is computed, and

ii) a non-iterative BF step is executed. The entirely process is a loop over each profile value. Inside the loop firstly the field filter kernel $s((f(\xi), f(x)))$ is constructed with parameters $\lambda$, $\alpha$ and initial estimator $m(x)$, and combined with the outlier filter kernel $c(\xi, x)$.

III. Verification

In order to ratify the MBF algorithm we analyze the filtering behavior on the measured scanline of the PTB Si111 profile [8]. The measurements used for the process were made using a ‘SIS nc-SFM Nanostation II’ (from Surface Imaging Systems GmbH, Herzogenrath, Germany). The dimensions used for measurements were $5 \mu m \times 5 \mu m$ with $512 \times 512$ pixels with an outlier (white spot on Fig.1) uptick 3387 nm in size [8].

Figures 2a-2c. show the p-profile and different filtered profiles. On Fig.2a. the Gauss filter and the ISO 13565 filter (by $\lambda = 0.8 mm$ cutoff) has been compared with MBF method (Fig.2.a). As shown in the zoomed area, the non-iterative filter does not respond to outlier and the Gaussian filter is the most sensitive in this configuration. In Figure 2b the regression filter behavior can be studied to analyzing the Gaussian filter and our non-iterative system characteristic. The regression filter response is 10 dB or 893 nm.

Figs 1. and 2. show the filtering by the software ProAssess and by the filter algorithms presented here (called as “New”).

$$m(x) = \frac{\int f(\xi) c(\xi, x) b((f(\xi), f(x)) \xi d\xi}{\int c(\xi, x) b((f(\xi), f(x)) \xi d\xi}$$
From the results in Table 1 for various filter kernels can be seen. Considerable similarity in the roughness parameters \( R_t, R_{\text{max}}, R_s, R_a, R_q \) was obtained (<1% RMS error), nevertheless in the case of \( R_{ak} \) and \( R_{ku} \) parameters, significant difference was received (<10 % RMS error).

**TABLE I.**

<table>
<thead>
<tr>
<th>MBF</th>
<th>Gaussian PTB 11562</th>
<th>Gaussian ProAss 11562</th>
<th>rob.Ga 0 order</th>
<th>rob.Ga 1 order</th>
<th>rob.Ga 2 order</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_t )</td>
<td>1.50</td>
<td>1.51</td>
<td>1.5</td>
<td>1.52</td>
<td>1.5</td>
</tr>
<tr>
<td>( R_{\text{max}} )</td>
<td>1.48</td>
<td>1.4</td>
<td>1.4</td>
<td>1.50</td>
<td>1.4</td>
</tr>
<tr>
<td>( R_s )</td>
<td>1.27</td>
<td>1.29</td>
<td>1.29</td>
<td>1.30</td>
<td>1.30</td>
</tr>
<tr>
<td>( R_a )</td>
<td>0.20</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
</tr>
<tr>
<td>( R_q )</td>
<td>0.25</td>
<td>0.23</td>
<td>0.23</td>
<td>0.24</td>
<td>0.24</td>
</tr>
<tr>
<td>( R_{ak} )</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>( R_{ku} )</td>
<td>2.70</td>
<td>2.8</td>
<td>2.8</td>
<td>2.8</td>
<td>2.8</td>
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</table>

**IV. CONCLUSION**

In this paper we have introduced the concept of noniterative Gaussian filtering for roughness surfaces. The filter is based on the modified bilateral filtering and is able to suppress outliers in a noniterative way.

The conclusion is that the Gaussian bilateral operator behaves morphologically always better like any other filter tested. After filtering the profile with outlier, the bilateral Gaussian operator skirts distortions.

The ISO 11562 Gaussian filter responds significantly to the outlier, while the performance of the regression filters are satisfactory. Table 1 shows the effect of outlier
on different values of the roughness parameters calculated by the RPTB software [8]. The greatest difference between the Gaussian bilateral operator and the other filter values is observed in the value of $R_{ku}$, otherwise the parameters are identical. The $R_{ku}$ value divides the filters. The bilateral Gaussian operator and the ISO 11562 Gaussian filter behave similarly otherwise the robust Gaussian operators belong to the other group.

V. REFERENCES


