

Noise in 3D Laser Range Scanner Data

Xianfang Sun

Paul L. Rosin

Ralph R. Martin

Frank C. Langbein

School of Computer Science
Cardiff University, UK



Introduction

- ❑ Noise is ubiquitous in measured data.
- ❑ Measurement noise is often assumed to be Gaussian white noise in many disciplines.
- ❑ *Real* 3D laser scanner noise is neither Gaussian nor white, according to our observations (even within a smooth surface).
- ❑ Denoising algorithms often depend on the noise model or assume a particular noise model.

Data Acquisition

- The scanner:
 - Konica Minolta Vivid 910
 - Claimed height accuracy: 50 μ m

- Test object used for scanning:
 - The higher the precision of the specimen, the more certain we can be that the noise is due to the scanning process.

 - A standard gauge block is too flat and polished. Measurements cannot be reliably obtained.

 - A slightly rough surface is needed to obtain satisfactory measurements.

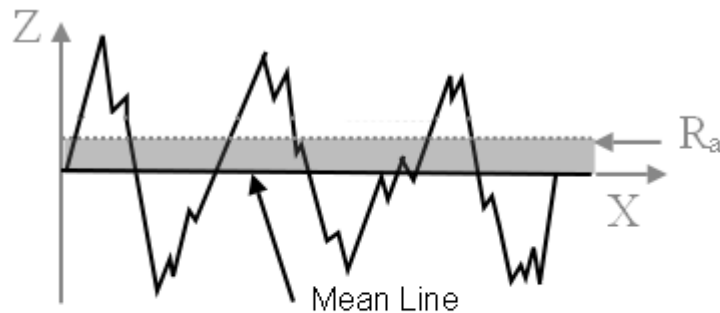
Data Acquisition (cont.)

- Our choice of test object:
 - Microsurf 315 N1 specimen (Rubert & Co Ltd)
 - Size $22.5 \times 15\text{mm}^2$
 - Flat on a *small* length scale
 - Mean roughness $R_a = 0.025\mu\text{ m}$ over 0.8mm
 - Mean roughness depth $R_z = 0.29\mu\text{ m}$ over 0.8mm
 - Thus, roughness \ll claimed scanner accuracy.

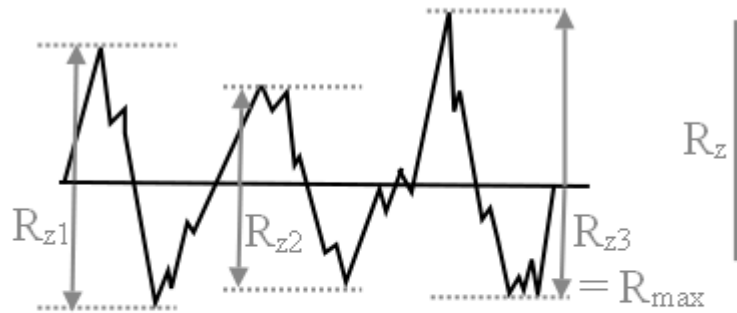
- Scanner data format: $\{x_i, y_i, z_i\}$
 - $\{x_i, y_i\}$ are gridded points on the surface with interval about 0.1734 mm.

R_a and R_z

- Two roughness parameters defined by ISO Standard 4287/1:1984
 - R_a : the arithmetic average of absolute values of roughness profile ordinates over sampling length
 - R_z : the arithmetic mean value of single roughness depth, taken over consecutive sampling lengths



$$R_a = \frac{1}{l} \int_0^l |Z(x)| dx$$



$$R_z = \frac{1}{n} \sum_{i=1}^n R_{z_i}$$

Data Preprocessing

- Trim off data near the edges of the test piece to avoid edge effects, leaving $125 \times 75 = 9375$ gridded points
- Fit a smooth surface (see next slide) around each surface point i in 3D space using the measurement data in some neighbourhood. The fitted surface is represented by

$$z = f(x, y, \mathbf{p})$$

where \mathbf{p} is a parameter vector depending on surface type

- Estimate the measurement noise e_i corresponding to each surface point i by:

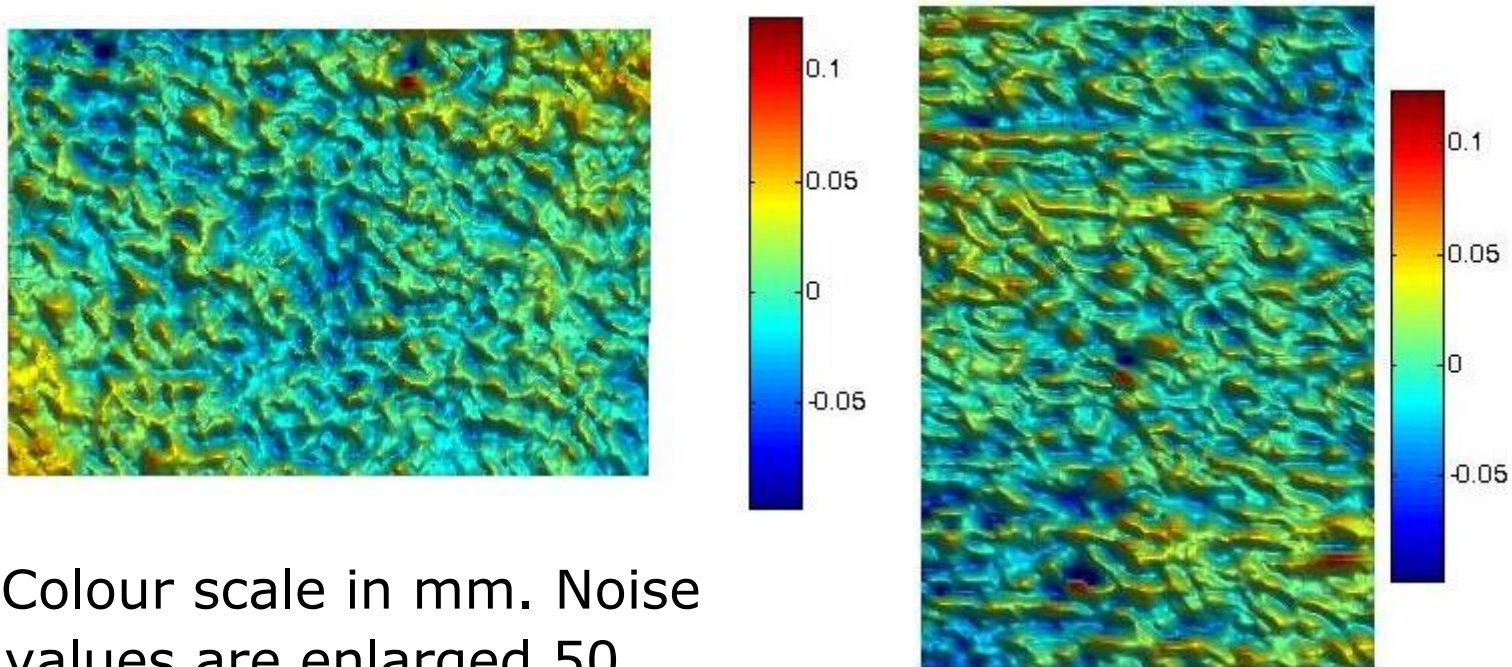
$$e_i = z_i - f(x_i, y_i, \mathbf{p})$$

Data Preprocessing (cont.)

- In fitting a smooth surface, we tried three alternative assumptions:
 - A1: A plane gives an adequate *global* fit to the data
 - A2: A quadratic surface gives an adequate *global* fit to the data
 - A3: No simple *global* shape model; a local procedural model is used based on iterative fitting of planes to data in local regions (see paper).

Data Preprocessing (cont.)

Extracted noise using global planar model,
measurements in two orientations



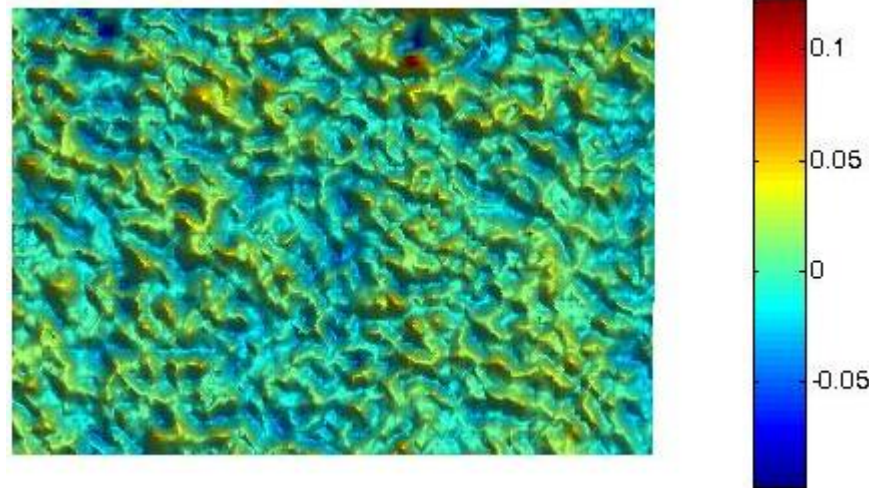
- Colour scale in mm. Noise values are enlarged 50 times for visualisation.

Data Preprocessing (cont.)

- ❑ Extracted noise from one orientation measurement shows apparent curvature.
- ❑ This may be due to actual curvature of the test surface *or* due to some systematic errors produced by the scanner.
- ❑ Measurement in a second orientation shows that the curvature is due to the test surface.
- ❑ A planar model is not a good fit for the overall surface.

Data Preprocessing (cont.)

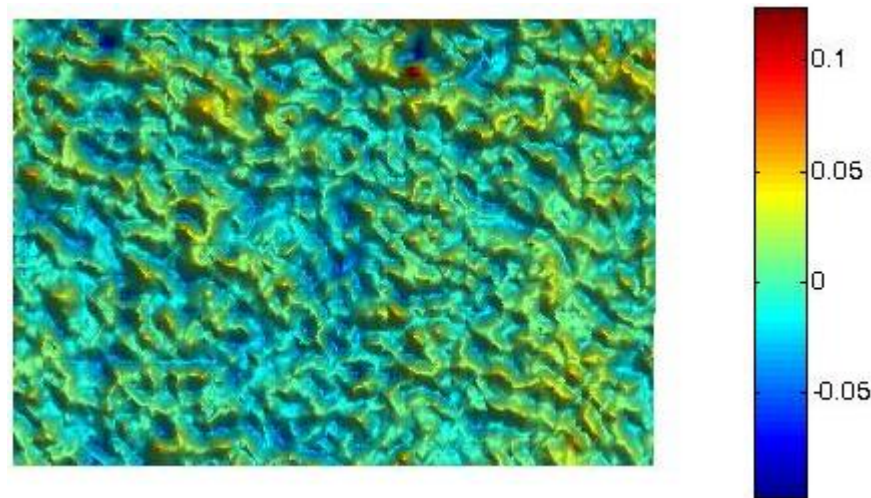
Extracted noise, global quadratic model



- ❑ Overall curvature is no longer present: it is a better fit than the planar model.
- ❑ Differences in residual errors when fitting quadratic (or higher order) surfaces are less than the roughness heights R_a and R_z of the test specimen. Thus a quadratic surface adequately represents the underlying surface of the specimen.

Data Preprocessing (cont.)

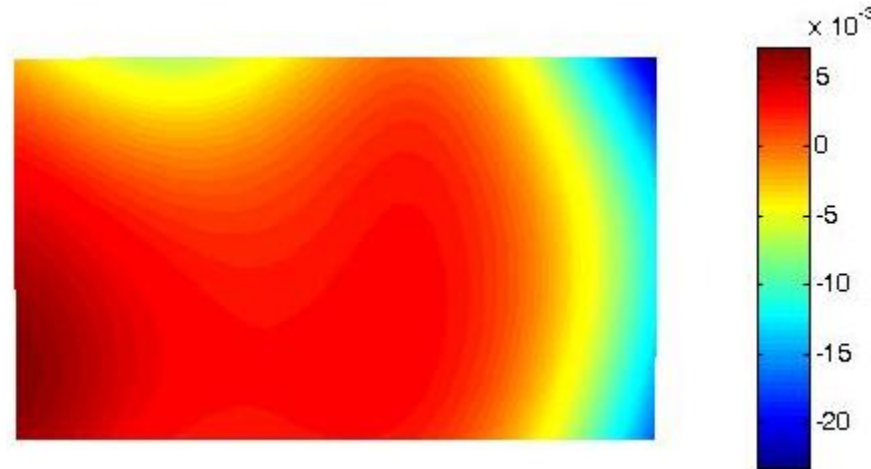
Extracted noise, iterative local fitting



- There is no significant difference between this result and that from quadratic model fit.

Data Preprocessing (cont.)

- Difference between A2 and A3



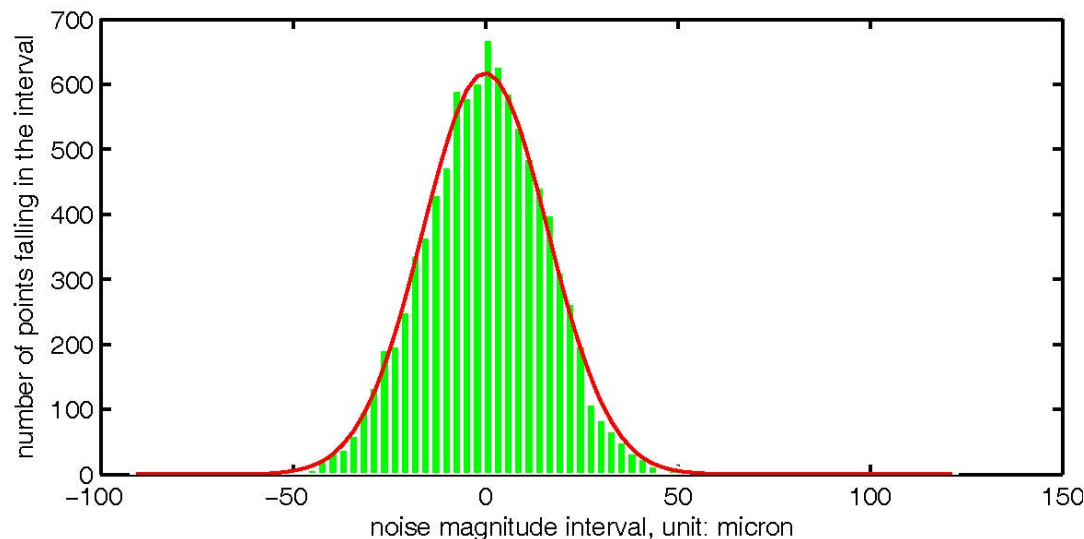
- The difference is slowly varying over a long distance with low amplitude

Noise Analysis- Quasi-Statistical Analysis

- We do statistical analyses on the extracted noise, not the real scanner noise, so we call our method *quasi-statistical* analysis of the real scanner noise.
- Because the extracted noise is an approximation to the real scanner noise within the level of the roughness of the test surface, the analysis results are reliable.

Noise Analysis- Quasi-Statistical Analysis

- Is the noise distribution Gaussian?

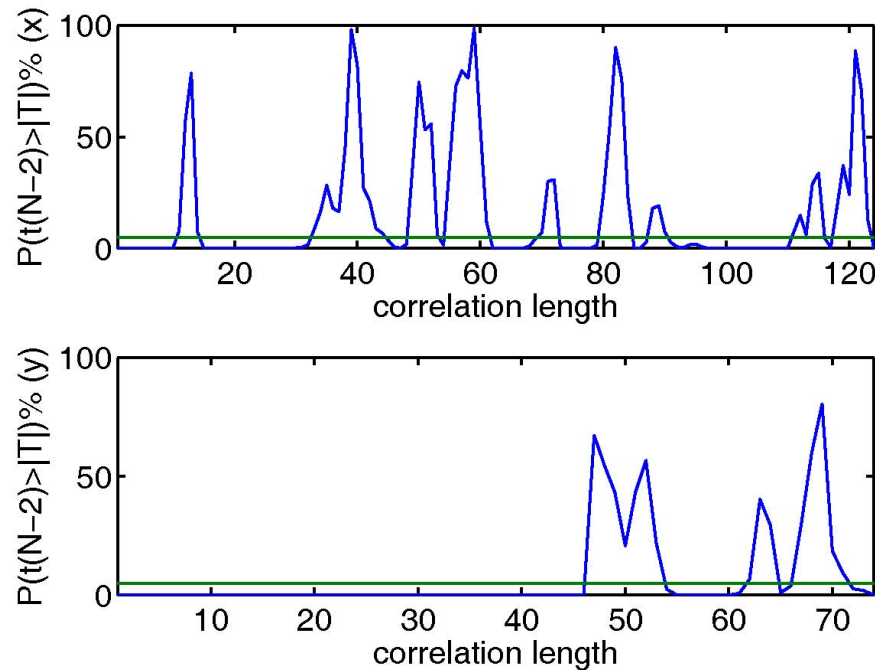


- Although the noise histogram appears to agree well with a Gaussian distribution, a χ^2 test shows that at a 5% significance level, **we should reject the hypothesis that the estimated noise distribution is Gaussian.**

Noise Analysis- Quasi-Statistical Analysis (cont.)

- Is the Noise Auto-correlated?
 - Although visually the noise looks auto-correlated, we still need to *statistically verify* the autocorrelation hypothesis.
 - Because the noise is not Gaussian distributed, we cannot perform a *t*-test on linear correlation coefficients to assess the autocorrelation.
 - We perform a nonparametric test: Spearman rank-order correlation coefficients in combination with a *t*-test.
 - Autocorrelation tests are performed along *x* and *y* directions separately.

Noise Analysis- Quasi-Statistical Analysis (cont.)



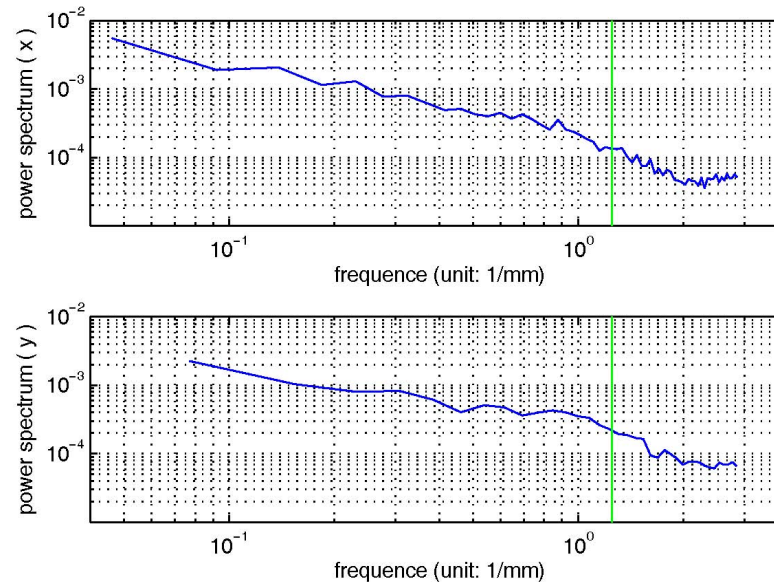
- Green lines show the 5% significance level for the t -test using Spearman rank-order auto-correlation coefficients. Correlation lengths whose probabilities lie over the green lines exhibit autocorrelation.
- **Overall, the estimated noise exhibits autocorrelation in both x and y directions for various correlation lengths.**

Noise Analysis- Fourier Analysis

- ❑ Quasi-statistical analysis is based on the estimated noise, not the real noise, hence we can only state that the above analysis provides a qualitative indication.
- ❑ Fourier analysis can directly analyse the real measurement data, and thus provide more reliable results.
- ❑ We first perform 1-D Fourier analysis to clearly show the autocorrelation in each direction, and then 2-D Fourier analysis to show more complex autocorrelation between x and y directions.

Noise Analysis- Fourier Analysis-1D

Power spectrum along x and y direction

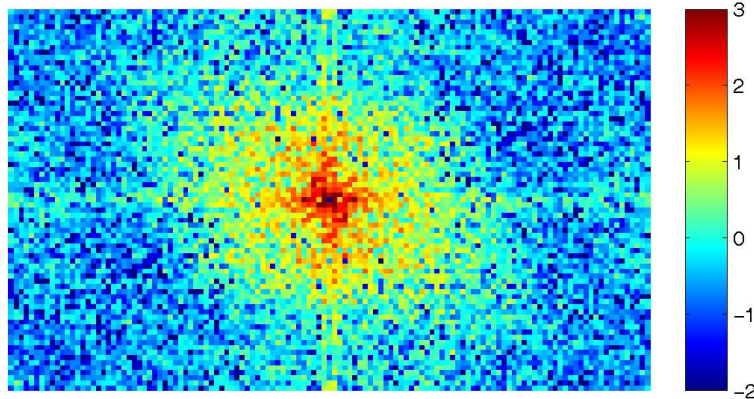


- The vertical green lines are at the frequency $f=1/0.8\text{mm}$, where 0.8mm is the sampling length for calculating the surface roughness of the test block.
- The surface roughness below the sampling length is negligible, thus the spectral power for frequency $f>1/0.8\text{mm}$ (to the right of the green line) is essentially due to scanner noise.

Noise Analysis- Fourier Analysis-1D (cont.)

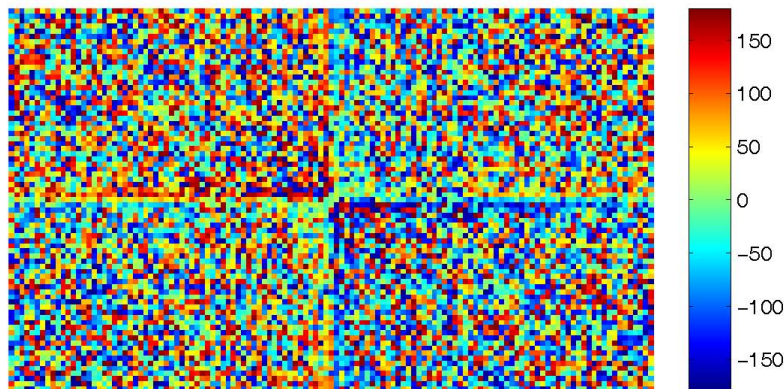
- Conclusion from 1D-Fourier analysis:
 - The measurement data are auto-correlated in both x and y directions since the power spectra are not *constant*.
 - Because the measurement data consist of both measurement noise and surface signal, the overall correlation could be from either the noise or the signal itself.
 - The right-hand side of the green line mainly reflects noise, and since it is not constant, the measurement noise is certainly not white (independent).

Noise Analysis- Fourier Analysis-2D



Logarithmic Magnitude of
Fourier spectrum

(zero frequency at centre
and high frequency towards
the boundary)



Phase of the spectrum

Noise Analysis- Fourier Analysis-2D (cont.)

- Conclusion from 2D-Fourier analysis:
 - Because the overall power spectrum is not constant, we again conclude as for 1D Fourier analysis that the measurement data are correlated in the x-y plane.
 - The phase of the 2D Fourier transform varies randomly with little regularity.

Noise Analysis-Summary

- The scan.
- The noise at each measurement point is not independent, but there are longer range interactions in the noise.

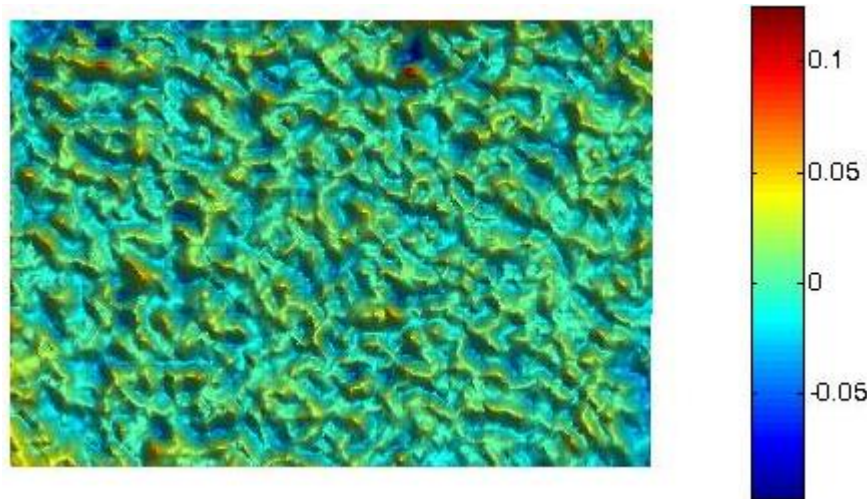
Noise Synthesis

- ❑ To numerically evaluate the effectiveness of denoising algorithms, we need some model for generating synthetic noise.
- ❑ Previous algorithms used Gaussian white noise for testing, which is not a good model.
- ❑ We use an inverse Fourier transform to generate synthetic noise.

Noise Synthesis

Inverse 2D Fourier Transform

- Original phase and original magnitude with low frequency components set to zero (to get rid of coarse surface shape).

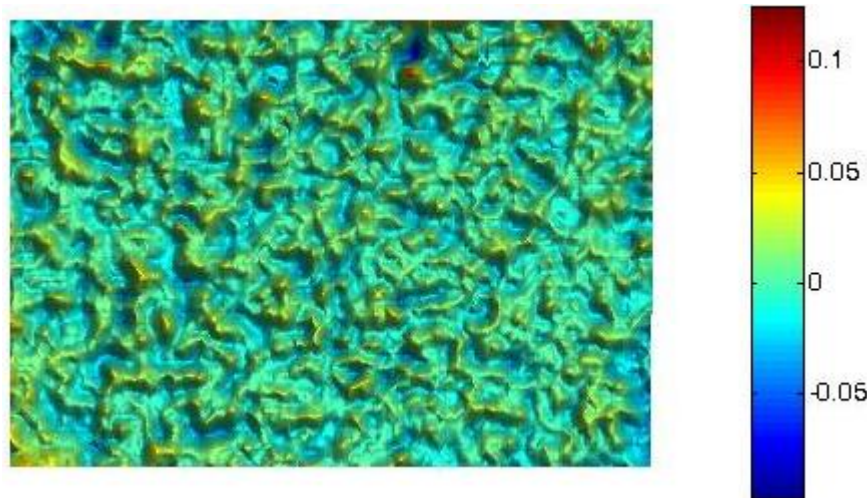


- The general structure of the original noise is preserved, while the obvious curvature of the specimen surface is removed.

Noise Synthesis

Inverse 2D Fourier Transform (cont.)

- Original phase and magnitude determined by a simple model (see paper) with low frequency components set to zero.

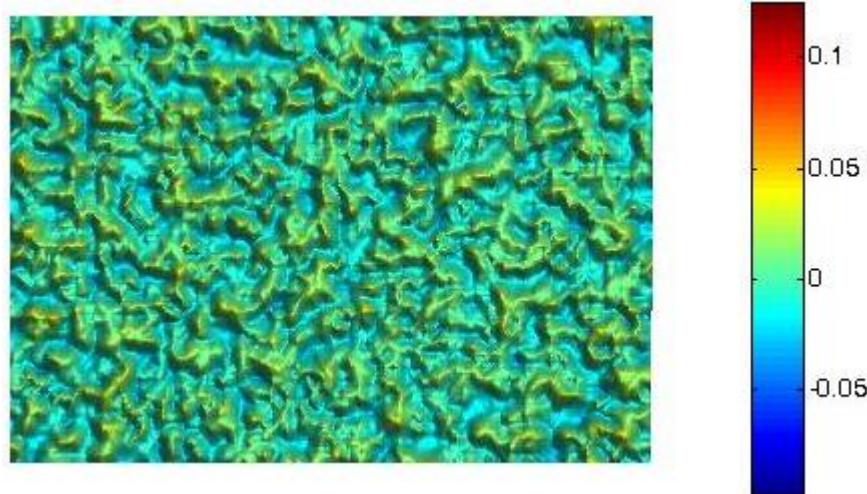


- This generated noise has a structure quite close to the original noise.

Noise Synthesis

Inverse Fourier Transform (cont.)

- Random phase, and magnitude determined by a simple model with low frequency components set to zero.



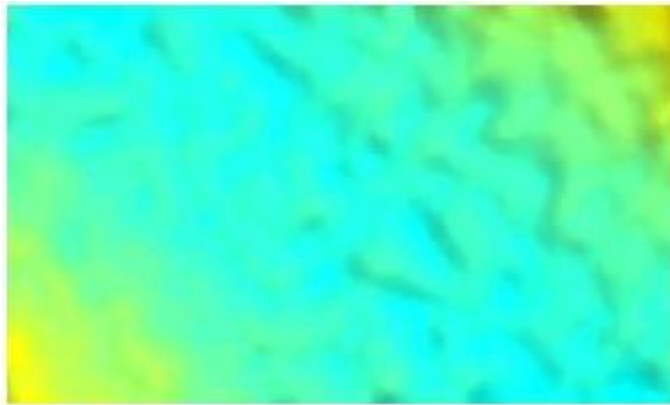
- This noise has structure yet further from measured noise, but the structure *is* similar to measured noise at least with respect to the magnitude, sizes, shapes and density of the bumps.
- This is a better method of generating synthetic noise than independent noise per measurement point.

Denoising experiments

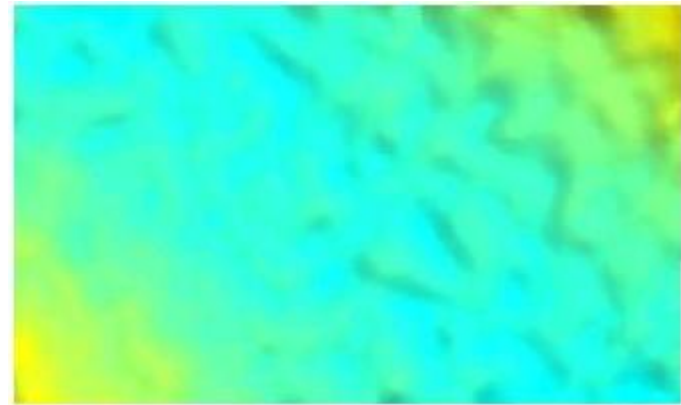
- ❑ Many people devising denoising methods have evaluated them using Gaussian white noise, not real noise, so their results are suspect.
- ❑ We now demonstrate the differences between the denoising results for surfaces with independent Gaussian noise and real noise.
- ❑ We use two typical denoising algorithms in our experiments:
 - the original Laplacian algorithm (Vollmer et al, 1999)
 - a recent feature-preserving algorithm (Sun et al, 2007).(The following slides give the number of iterations used).

Denoising experiments-

Gaussian white noise



Laplacian, 10



Feature-Preserving, 10

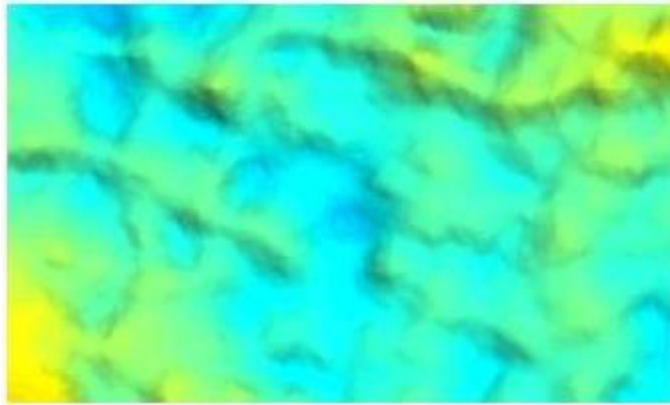


Laplacian, 50

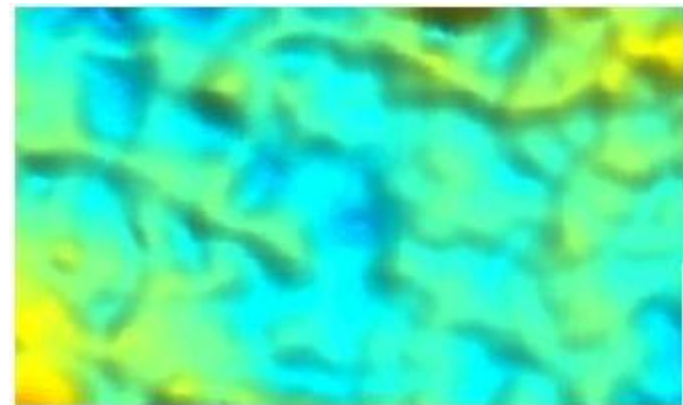


Feature-Preserving, 50

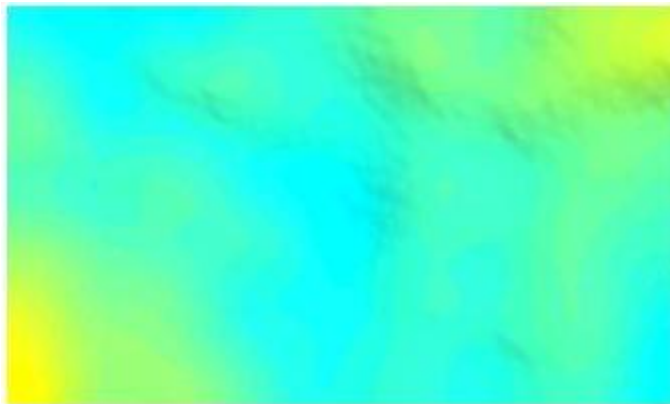
Denoising experiments- Real scanner data



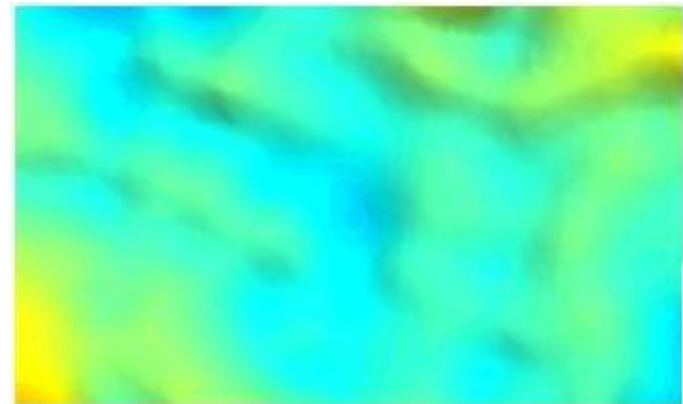
Laplacian, 10



Feature-Preserving, 10



Laplacian, 50



Feature-Preserving, 50

Denoising experiments- Summary



- ❑ Fewer iterations of denoising algorithms are needed to remove Gaussian white noise than to remove real scanner noise.
- ❑ Denoising algorithms are generally less successful at removing the structural features present in real scanner noise.
- ❑ Feature-preserving algorithms have more difficulty than non-feature-preserving algorithms in removing structural features in real scanner noise.
- ❑ Many previous papers claiming good smoothing results based on experiments with synthetic noise are over-optimistic in their assessment of their ability to remove real scanner noise.

Conclusions

- ❑ Real scanner noise is *not quite Gaussian*, and more importantly, shows *significant correlation* from point to point.
- ❑ Inverse discrete Fourier transforms plus a simple model can be used to generate fairly realistic synthetic noise.
- ❑ It is more difficult to remove noise from real measurement data than from synthetic data with Gaussian white noise.
- ❑ Future denoising algorithms should take into account the real nature of scanner noise.