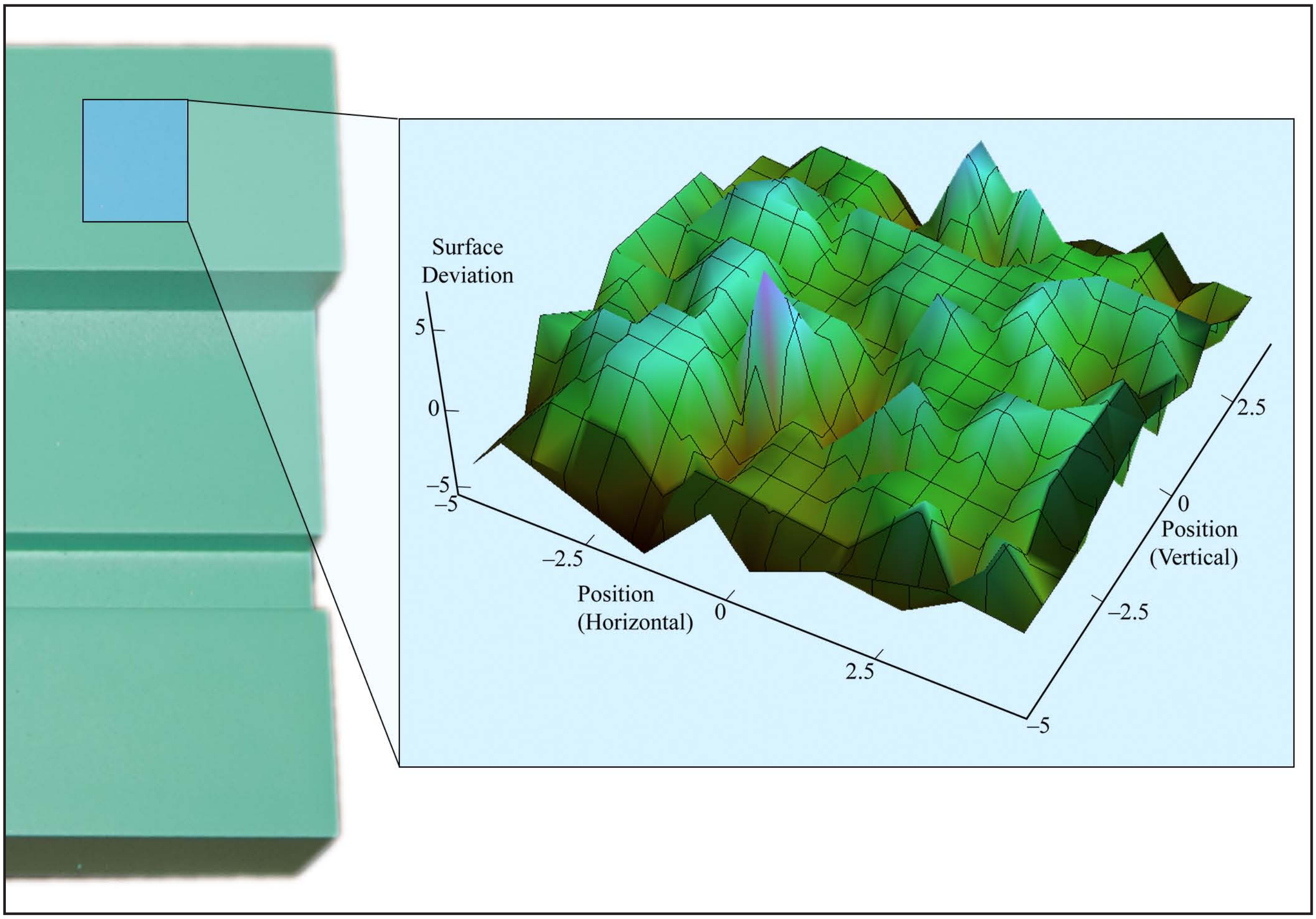

Enhanced Surface Metrology

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The constant search for more accurate measurement generally leads to higher cost, greater complexity, and/or devices that do not lend themselves to manufacturing environments. For example, surface metrology can be accomplished by a number of methods, ranging from rulers and visual estimation (cheap, fast, and inaccurate) up to fixed coordinate measuring machines (expensive, slow, and accurate). The tradeoffs involved in selecting metrology methods generally involve these three parameters of cost (initial and operation), measurement speed, and accuracy. We present a method of adding one more tradeoff: measurement precision (perpendicular to the surface) vs. sampling resolution (along the surface). Through application of statistical sampling and curve fitting, we can improve precision by approximately the square root of the amount that we decrease resolution.

We applied this technique to a number of known and unknown targets, using the Cognitens WLS400 white-light stereovision system from Hexagon Metrology and a custom laser interferometry measurement system. Using the enhancements described in this article, we were able to improve the measurements significantly. Measurement of a flat reference surface, for example, was enhanced by reducing noise by a factor of 11 and improving surface measurement accuracy 2× (limited by the actual surface figure). An application of this technology to a known sphere reduced noise by a factor of eight and demonstrated that the sphere was within its surface and diameter specifications. We used this statistical technique to reduce noise in an interferometry system 15×, and demonstrated that the supposedly flat surface had deviations exceeding 16 percent over a square region 1 cm on a side. Finally, we modeled the white-light scanner to determine its probability of identifying small surface features. Based on this model, we found that statistical noise reduction can improve the minimum resolvable feature height by a factor of five without significant difficulty.

BACKGROUND AND THEORY

Metrology is the science of measurement. For the purposes of this work, we concentrate on dimensional measurement of surfaces (surface metrology). There are many ways to measure the dimensions of a surface, to map the actual item being measured into a mathematical abstraction. In the methods described in this article, the map of the surface is in the form of a point cloud—a number of points located in three-dimensional space, each of which corresponds to a point on the surface of the item. Once these points are measured, the resulting point cloud can be manipulated in a number of ways to produce a surface map. The points can, for example, be used as the vertexes of triangles or other polygons (a version of this is used for an .STL file). An approximate surface may be constructed by combining a number of points into a single polygonal area with a polynomial surface description using some interpolation system such as non-uniform rational basis spline (NURBS). Alternatively, a regional (rather than local) surface can be modeled, with adjacent regional surfaces being required to match mathematically. Many other methods are possible as well.

Often, the expected shape surface being measured (the nominal surface) is known, whether the surface is simple (such as a plane, cylinder, or sphere, or combination thereof) or complex (in which case there may be a CAD file to describe the nominal surface). In these cases, the measured surface may be described in terms of its deviation from CAD (or its "actual minus nominal" values). Furthermore, these deviations may be due to any combination of three causes: first, the real surface deviation from nominal, δ_r; second, consistent measurement inaccuracies, δ_m; and third, random measurement inaccuracies or other random noise, δ_n. The real surface geometry may be described in terms of (ξ, η, ζ) coordinates, where ξ and η are in the plane of the local surface and ζ is perpendicular to this. Locally, then, ξ, η, and ζ correspond to x, y, and z. At any point (ξ, η), the real surface "height" is then expressed as

$$\zeta = \zeta_0 + \delta_r \qquad \text{(Equation 1)}$$

where ζ_0 is the nominal value of the surface at (ξ, η). The actual surface, then, is described by a point cloud corresponding to (ξ, η, $\zeta_0 + \delta_r$).

To have the best possible description of the actual surface, the other two deviations must be reduced. Consistent measurement inaccuracies (δ_m) can be removed through careful calibration, or at least reduced to arbitrarily small values. They will be ignored in this article. Noise (δ_n), on the other hand, cannot be eliminated. It can reduce the accuracy of measurement and can mask features, as seen in figure 1. This article is concerned specifically with noise reduction and its effects on the measurement.

In the model of figure 1a, a 10 mm × 10 mm portion of a surface, nominally spherical, can be seen. The surface only ranges over 10 μm in this area. In figure 1b, the same surface is seen with a slight defect, whose height is ~1.5 μm. This is the real surface, the nominal plus the real deviation. However, in the presence of a small amount of measurement noise ($3\sigma = +/- 0.9$ μm), figure 1c shows that the surface figure is more difficult to estimate, although the defect can still be seen. In figure 1d, the noise has been increased to $3\sigma = 3$ μm, twice the size of the defect. Although it is possible to see that the underlying surface is curved, the defect is not visible.

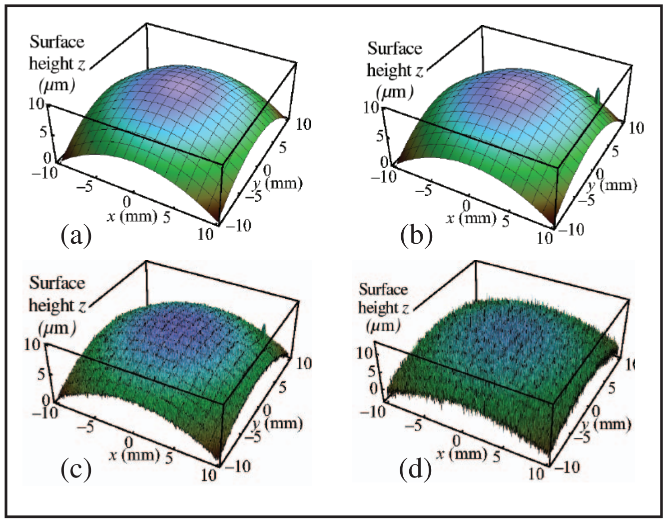

Figure 1. Nominal surface (a) has a defect (b), still visible with low noise (c), but hidden by moderate noise (d)

Noise reduction by statistical methods

From the previous section, it is clear that the measured value at any point on the surface is

$$\zeta_{meas} = \zeta_0 + \delta_r + \delta_n \qquad \text{(Equation 2)}$$

It is possible to apply a number of statistical noise-reduction methods to equation 2. They generally reduce to weighted averaging, in which a noise-reduced value is calculated from a range of nearby points, as seen in equation 3:

$$\zeta_{calc}(\xi_0,\eta_0) = \frac{\sum_{m=-M/2}^{M/2}\sum_{n=-N/2}^{N/2} w_{mn}\zeta_{meas}(\xi_0+m,\eta_0+n)}{\sum_{m=-M/2}^{M/2}\sum_{n=-N/2}^{N/2} w_{mn}} \qquad \text{(Equation 3)}$$

where w_{mn} are the statistical weights. In the simplest case, all the w_{mn} are 1 over the summation range (and 0 outside it), resulting in:

$$\zeta_{calc}(\xi_0,\eta_0) = \frac{\sum_{m=-M/2}^{M/2}\sum_{n=-N/2}^{N/2} \zeta_{meas}(\xi_0+m,\eta_0+n)}{(M+1)(N+1)} \qquad \text{(Equation 4)}$$

In equation 4, the arithmetic mean of the surface values in the range $\xi_0 - m/2 \le \xi \le \xi_0 + m/2$ intersected with $\eta_0 - n/2 \le \eta \le \eta_0 + n/2$. In general, it is safe to assume that the three parts of equation 2 are completely independent; in other words, the real deviations from nominal are not correlated with the nominal values, and the noise is truly random. Based only on this, we can separate equation 4 into:

$$\zeta_{calc}(\xi_0,\eta_0) = \zeta_0 + \delta_r + \frac{\sum_{m=-M/2}^{M/2}\sum_{n=-N/2}^{N/2} \delta_n}{(M+1)(N+1)} \qquad \text{(Equation 5)}$$

If we make the further assumption that the noise values follow a normal distribution (usually a good assumption), the expected noise value (based on the statistical standard deviation) is significantly reduced; if σ_{meas} is the noise figure for a single measurement, the noise resulting from the calculation of equation 5 is:

$$\sigma_{calc} = \sigma_{meas} \Big/ \sqrt{(M+1)(N+1)} \qquad \text{(Equation 6)}$$

For statistical methods other using $w_{mn} \ne 1$, the calculation is equally straightforward.

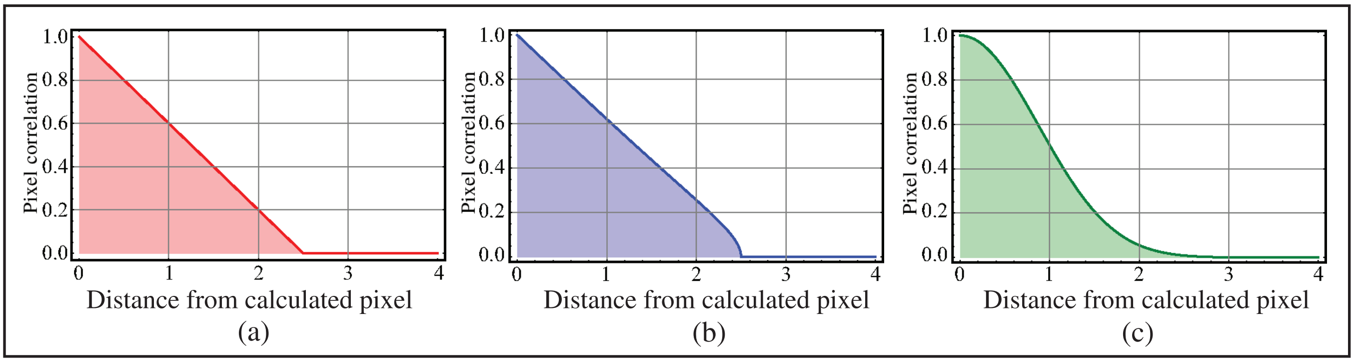

Figure 2. Correlation induced by statistical noise-reduction processes, shown assuming statistical range of 5 pixels for (a) square mean sampling, (b) circular mean sampling, and (c) Gaussian-weighted sampling

Specific methods of noise reduction

We studied several methods of statistical noise reduction; in this article, we discuss three. The simplest method is generating the arithmetic mean over a square sampling area. In this case, referring to equation 3, $w_{mn} = 1$ and $M = N$. The expected noise reduction is a factor of M. The second method is the arithmetic mean, but over a circular region. This can be described (statistically) as $w_{mn} = 1$ over the range $m^2 + n^2 \leq (M/2)^2$, again with $M = N$. This statistical process uses 78.5 percent as many samples as the square, and is expected to reduce noise by a factor of $0.886M$. The final method is a Gaussian sampling process over the same square region (again, $M = N$). In this case, the sampling weights are Gaussian;

$$w_{mn} = e^{-2\left(m^2+n^2\right)/\left(M/2\right)^2} \qquad \text{(Equation 7)}$$

The noise-reduction value is only a factor of $0.598M$, but the correlation among points is lower; the noise reduction can be increased by increasing M, which is safer in the Gaussian process than in the other two described here.

Obviously, when several measurements are combined statistically, the result includes statistical correlation among the calculated values. This leads to a reduction in image contrast. As seen in figure 2, using $M = 5$, using the mean value over a square area leads to correlation that declines linearly with pixel distance (as seen in figure2a). Likewise, using the mean value over a circular area leads to correlation that is nearly the same, but slightly higher near M/2 (as seen in figure2b). The Gaussian smoothing (seen in figure 2c) has less correlation and is smoother.

Detecting small features

One of the most important parameters of a metrology system, particularly in application to nondestructive testing, is its capability to find small features or small deviations from nominal. In a recent project, the goal was to find defects whose height was 3 μm and whose diameter was 3 mm. To predict the probability of locating this type of defect, we applied the targeting task performance (TTP) model developed for predicting the performance of night vision systems.[1] We modeled a metrology system based on the Cognitens WLS400, using 6 μm for the noise standard deviation. Using the TTP model, we discovered that such a system has a minimum feature detection height of 3.5 μm (without noise reduction). We modeled the three statistical noise-reduction methods described above, in each case using 1 mm as the range (we applied the arithmetic mean method to a square 1 mm on a side and to a circle of diameter 1 mm, and we used the Gaussian-weighted method with equivalent range 1 mm).

Using the TTP standard requirements for identification—recognizing a feature and being able to tell it apart from similar features—we found that the modeled metrology system could identify the small defect with a probability of 92.5 percent for noise detection using a square sampling region, 91.4 percent for a circular sampling region, and 75.5 percent if the Gaussian-weighted method was used. We predicted the probability of identifying a feature 3 μm high, as a function of feature size (as seen in figure 3). The TTP method describes a "characteristic feature size" as the square root of the feature area; this avoids shape-based detection methods.

The square- and circular-mean noise-reduction methods have very similar probability curves; the greater noise reduction using the square sampling region is balanced by the lower correlation among pixels using the circular method. The Gaussian-weighted method's even lower correlation is not sufficient to make up for its lower noise reduction. Even the Gaussian method, however, can identify a 3-μm feature 2.5 mm in extent with 50-percent probability, while the metrology system without noise reduction cannot identify any 3-μm features. The small feature capabilities should be investigated further, together with using Gaussian-weighted noise reduction over a larger area.

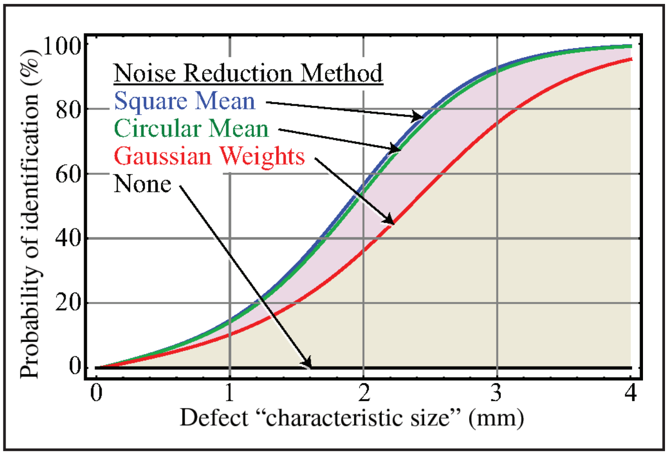

Figure 3. Probability of identifying a 3-μm feature with no noise reduction (black), Gaussian-weighted noise reduction (red), circular-mean noise reduction (green), and square-mean noise reduction (blue)

EXPERIMENTS

To test this theory, we took data on three samples: two were flat and one was spherical. One of the flat samples and the spherical sample were measured using the Cognitens WLS400 white-light system using the large field of view; the third sample was measured using simple laser interferometry (to test the enhancement method with speckle). The noise-reduction method used was the arithmetic-mean method, with a circular sampling area used on the sphere and a square sampling area on the two flat samples.

Measurement methods

The two measurement systems used were the Cognitens WLS400 and a breadboard Mach-Zender interferometer. The WLS400 can be configured as a manually operated system (designated the WLS400M—the configuration we used) or an automated system (WLS400A). The metrology system and measurement specifications of these configurations are identical. The WLS400 is a white-light stereovision system with three cameras, 4.0 MPix each, mounted in a triangular pattern. The stated accuracy of this system is 30 μm over 1 meter at 2σ. The stated measurement volume of a single shot is 500 mm wide, 500 mm high, and 230 mm deep, centered at 780 mm from the measurement head (large field of view). Laboratory measurements (not stated accuracies) of a number of objects indicated that the measurement noise within a single shot, which relates to the noise-reduction method of this article, can be described by a standard deviation of +/– 6.0 μm (which would correspond to a 2σ span of 24 μm).

The interferometer used a laser operating at 532 nm and had arm lengths of 350 mm. The relative arm alignment was accurate to +/– 0.7 μr. Each fringe period (from dark to dark) represents half a wavelength of the laser, or 266 nm, in the out-of-plane direction. Speckle is calculated to average 16.2 μm in diameter, spaced at 31.6 μm, in this system.

Flat sample, WLS400

The first sample used, as seen in figure 4, was a block, which was made of ceramic and had a polished white surface finish. The area shown in blue was selected for noise reduction. The fit area was 300 mm × 75 mm. The artifact was positioned to be in the far range of the WLS400 and data were taken from a 45° angle; between those and the polished surface, this is a worst-case artifact for white-light metrology. The nominal surface is a plane, so we matched the measured data to a plane using two-dimensional linear regression, and defined this plane as our nominal value.

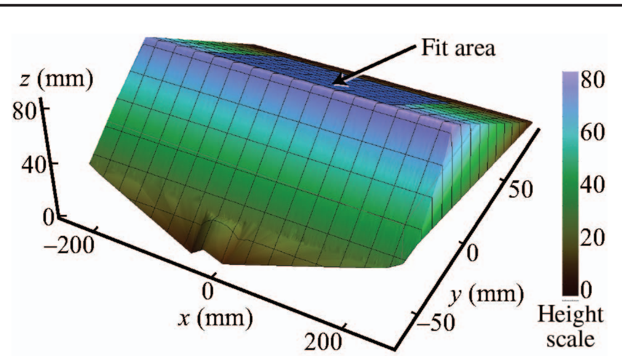

Figure 4. Block used as flat sample for WLS400 test

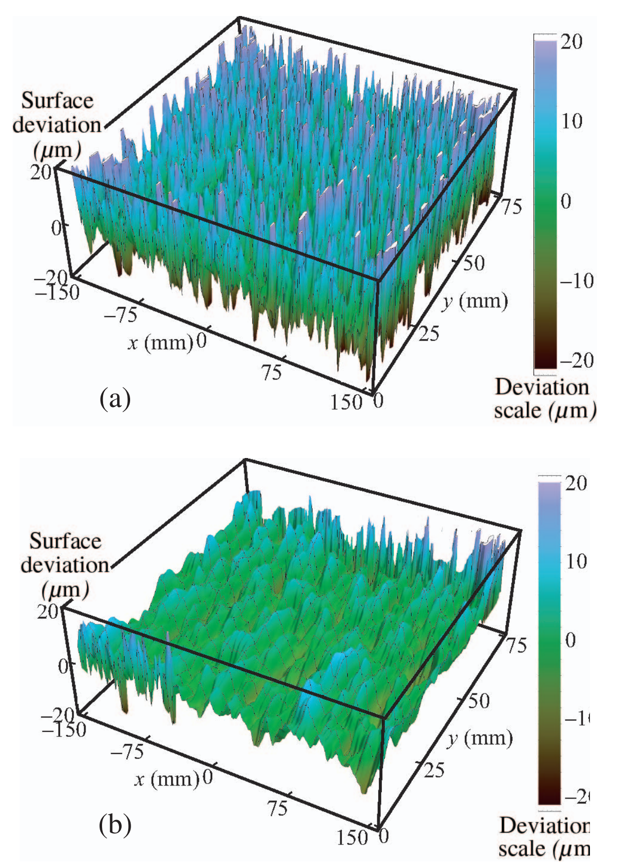

Figure 5. Measurement noise and actual surface deviation, before (a) and after (b) statistical noise reduction

The difference between the measurements and the best-fit plane in the test area was taken for each of the 52,107 samples in the point cloud. The mean difference between measured and nominal was 0.19 pm, exceptionally close to zero. The standard deviation of these residuals was 9.30 μm, and the 3σ point range was +/–37.2 μm. This is slightly larger than three times the standard deviation because the errors at the edges were larger than those at the center, as seen in figure 5. The regular surface ripple seen in figure 5b indicates that these larger errors may be a surface feature. Because of the angle of measurement, the measurements in the left and right corners of figure 5b represent a worst-case approach, near the ends of the measurement volume.

We used the arithmetic-mean noise-reduction method with a square sampling region 11 pixels (2.86 mm) on a side, for a random noise reduction of 11×. The residuals after noise reduction had a mean value of 39.5 nm, still very small. The standard deviation of the residuals was 4.55 μm, a factor of 2.04 better than before noise reduction, and the 3σ point range was +/–20.8 μm, an improvement of 1.79×. Using statistical analysis, this indicates that the standard deviation of the real surface deviation from nominal was +/–4.49 μm over this area, while the measurement noise standard deviation was +/–8.14 μm.

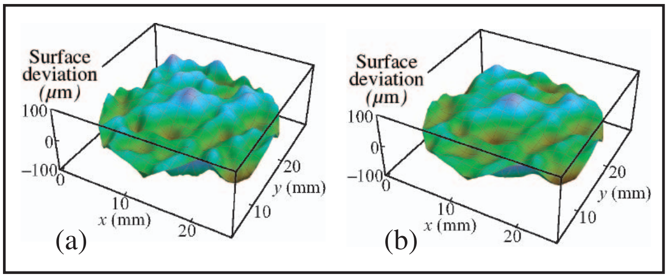

Figure 6. Surface deviation residuals before (a) and after (b) noise reduction

Sphere sample, WLS400

The next test was on a known sphere, whose diameter was specified to be 1.5000 +/–0.0001 in., but whose surface was specified smooth only to +/–0.001 in. We scanned a section of the upper half of the sphere, a circular area whose diameter was 27.20 mm. Based on the specification, we used a nonlinear least-squares method to fit a sphere of radius 19.050 mm (0.75000 in.) to the data and defined that as nominal. The mean value of the raw residuals (measured points minus nominal) was 0.987 μm and its standard deviation was +/–18.4 μm.

We applied the arithmetic-mean noise-reduction method with a circular sampling area, with a radius of 1 mm. This included, on the average, 64 points in the cloud, which resulting in random noise reduction of a factor of eight, as seen in figure 6.

Applying the statistical process to the sphere data resulted in mean residual value of 0.873 μm, and standard deviation of +/–15.8 μm. This is only a reduction of 14.1 percent in the residual value, because the larger portion of the deviations from nominal is the real surface deviation, rather than the measurement noise. The low value of the mean, however, indicates that the diameter of the sphere is measured to be accurate. The surface of the sphere, colorized to show deviation from nominal, appears in figure 7.

Interferometric measurement

Next we measured a nominally flat, metallic surface (aluminum), mechanically polished to $R_A \approx 60$. We used a Mach-

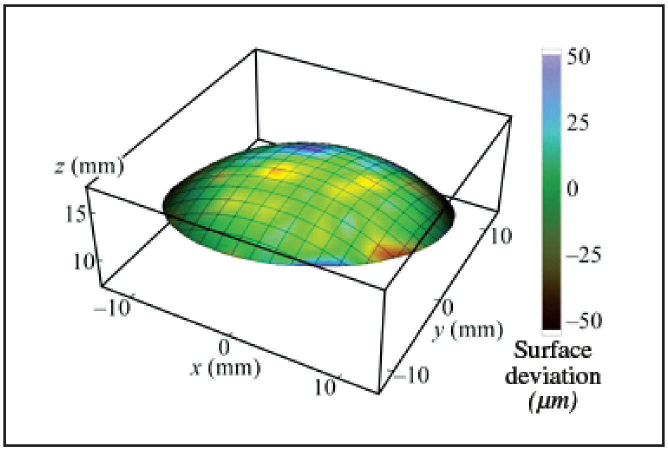

Figure 7. Surface of the sphere with locations measured from its center; surface color shows deviation from nominal (after noise reduction)

Zender interferometer to obtain an interferogram covering a square 1 cm on a side, as seen in figure 8. The illumination wavelength was 532 nm. Because the illuminator was a laser, there is considerable speckle noise; it would be much easier to see the interferogram if the speckle noise were reduced. Speckle is different from other noise sources in that, while its location is random, the size of each spot is relatively uniform.

The first step in reducing the noise is to find best-fit nominal data. From interferometry theory, we know that a perfect, noise-free interferogram would produce intensity that fits

$$I(x,y) = I_0 \frac{1}{2}\left[1+\sin\left(2\pi\frac{x}{T}+\phi\right)\right] \qquad \text{(Equation 8)}$$

where I_0 is the maximum illumination (and what is shown in the intensity pattern is I/I_0), T is the period of the fringe pattern, and ϕ is a phase factor that moves the fringe pattern right or left. There is no dependence on y because the interferometer was aligned with the y direction.

The sinusoidal best fit had a period of 2.39 mm, indicating a slope of 111 μr (23.0 arc seconds). The difference between the measured data of figure 8a and the best fit of figure 8b, shown in figure 8c, is not fully random. The mean value of these residuals is 9.67 percent, indicating that there is a significant amount of real surface deviation from the nominal. The standard deviation of the deviation is 18.6 percent. After noise reduction using arithmetic mean over a square sampling region 0.167 mm on a side, the appearance of speckle has been reduced, as seen in figure 8d. The mean value has remained virtually constant at 9.70 percent, demonstrating that the noise reduction only operated on genuinely random noise. The reduced standard deviation was 16.1 percent, indicating that the real surface deviation was 16.0 percent and the random noise was 9.35 percent.

SUMMARY AND CONCLUSIONS

We have developed a statistical method for noise reduction of three-dimensional metrology systems. The method involves a combination of measurement values over a range of points, and permits weighting the points (enabling the user to, for example, assign confidence values to the various measurements). Applying this to the Cognitens WLS400 white-light metrology system, we applied an unweighted 11 pixel × 11 pixel sampling region to a flat surface, and reduced the deviation from nominal by more than a factor of two. Using statistical methods to separate random noise from actual surface variation, we determined that the standard deviation of the actual surface (compared to nominal) was +/–4.49 μm over the measured 300 mm × 75 mm region. Measurements of a sphere whose diameter was nominally 1.5000 in. found that the diameter was extraordinarily accurate. The surface was specified to fit a sphere to an accuracy of +/–25.4 μm, and we measured that its accuracy was +/–15.8 μm, using unweighted noise reduction over a circular area of 2-mm diameter. We then applied the noise-reduction technique to an interferometric measurement with speckle noise. We were able to reduce the appearance of noise in the

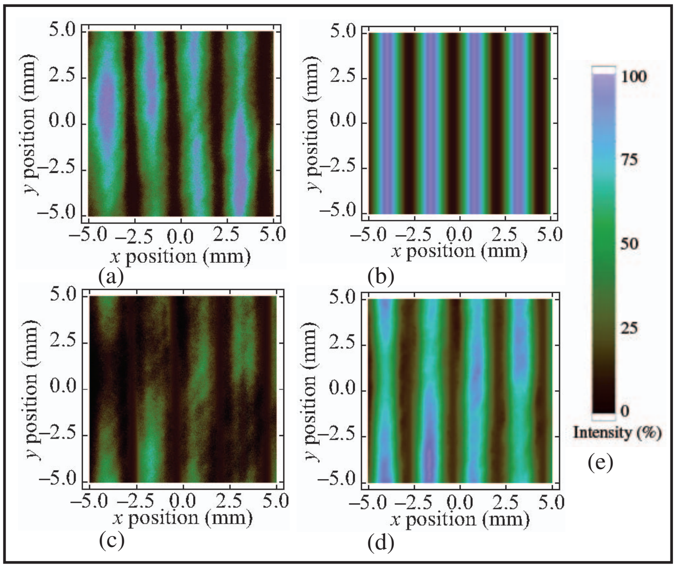

Figure 8. Noise reduction in interferometry: the original interferogram (a) was fit to a sinusoid with intensity varying from 0 to 1 (b); the difference between these two is the noise pattern (c); after noise reduction, the interferogram is much clearer (d); all follow the scale (e)

image, and determined that the surface deviated 16.0 percent from perfect flatness over the 10 mm × 10 mm region measured, using unweighted noise reduction over a square region 167 μm on a side.

We also modeled a metrological system similar to several that are commercially available to determine their capabilities for identifying small features. We discovered that, although the statistical noise reduction induces correlation among nearby points, the reduction in noise more than makes up for this when identifying small features. Our modeled system, for example, was limited to features whose characteristic size was about 3.5 μm and larger, while statistical processing reduced this minimum identifiable size to 2.0 μm for Gaussian-weighted noise reduction with 5-pixel range, 0.75 μm for unweighted noise reduction over a circular region of 5-pixel diameter, and 0.66 μm for unweighted noise reduction over a square region 5 pixels on a side. These improvements indicate that the statistical surface metrology enhancement method can be useful in detecting small features.

REFERENCES

[1] Vollmerhausen, R.H.; Jacobs, E.; and Driggers, R.G., “New Metric for Predicting Target Acquisition Performance,” *Optical Engineering*, Vol. 43, No. 11, pp. 2806-2818, 2004.