

SIMULATION OF ADAPTIVE SAMPLING IN PROFILE MEASUREMENT FOR STRUCTURED SURFACES

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ABSTRACT

Adaptive sampling is a novel sampling design that can redirect sampling effort during a survey in response to the observed values. Its application on surface texture measurement is new, such as working with stylus profilometers. As a start, this paper focuses on a classical one-dimensional adaptive sampling in surface texture measurement for structured surfaces. The sampling simulations show that both the reconstruction accuracy and repeatability have a significant improvement compared to the uniform sampling – the most prevalent strategy at present.

Keywords: adaptive sampling, uniform sampling, profile measurement, structured surfaces

1 INTRODUCTION

It is well known that uniform sampling is the current mainstream sampling method in surface metrology and is employed in all the current areal surface measurement instruments [1]. However, along with the development of the structured surfaces which is recognized as more and more important, some intelligent sampling methods in surface measurement are brought forward. There are many different intelligent sampling methods at present which are usually non-uniform. Among them, “adaptive” sampling is an important branch because of its robust flexibility to a wide range of complex surfaces. Many scientists [2-5] in CMM industry have contributed on this field. Some of the methods have been demonstrated to work very well in scanning CMM for its flexible sampling path design. However, in surface metrology which is oriented to surface texture measurement in micro or nano scale, instrumentation limitation (for example the fixed uniform CCD pixel structure) determines the difficulties of the technique transfer. Development of the intelligent sampling methods for surface metrology instruments has a unique situation.

As the mainstream of surface measurement, uniform sampling has been widely used in industry and scientific research such as precision engineering and biomedical analysis. An important viewpoint about the popularity of the uniform grid is that there is a reluctance to using anything other than a rectangular sampling scheme because it is perceptually more satisfactory for humans to observe straight vertical features on a square grid pattern [6]. Computing convenience benefits from the uniform grid sampling as well for example, it is very simple to move from a 1D FFT to a 2D FFT simply by taking all the rows in turn and then the columns, i.e. using the tensor product surface method [7].

Along with the development of structured surfaces which is firstly strictly defined by Evans in 1999 [8], it is recognized that intelligent sampling methods are in need in surface texture measurements. Such surfaces are usually designed to provide special functions such as self-cleaning, wide spectrum light absorption and good heat transfer. Their surface textures are dominated by deterministic features rather than random imperfections. Because of the interest on structured surfaces is no longer the single roughness or form error, but rather the dimensional parameters are of more importance, intelligent sampling methods are required to make the measurement more efficient and accurate.

One-dimensional adaptive sampling (profile measurement) is simulated in this study. It is known there are many different adaptive sampling methods and a single method can derive different sampling results because of the uncertainty of setting the starting sampling point or other pre-defined conditions. It has been shown [9] that for any iterative method, the final result is sensitive to the starting conditions. Therefore it is still a question that how stable adaptive sampling is compared to uniform sampling, though the method is expected to provide more accurate results. In this paper, working with the first degree spline reconstruction, the reconstruction accuracy for adaptive sampling is computed. By randomly setting initial conditions, the sampling repeatability is also analyzed.

2 THE ALGORITHM

If we can identify the regions of the signal with frequencies higher than the Nyquist limit, we can take additional samples in those regions without needing to incur the computational expense of increasing the sampling frequency everywhere [10]. This is the basic premise of adaptive sampling. However, it is hard to find all the places where extra sampling is needed in practice if the CAD model of the signal is not given at the beginning. Even though a CAD model can be given in advance, the positioning error between the theoretical model and the practical work-piece is hard to control. Many proposed detecting techniques [2, 11] are based on examining adjacent sample values and finding places where there is a significant change in value between the two; the assumption is that the signal has high frequencies in that region [10]. Therefore, it is still the question to establish a robust technique to find the key places to be over sampled and the number of extra sampling points demanded.

Nevertheless, in this study, the aim is to transfer the current adaptive sampling techniques to the surface metrology. Shih et al [2] developed an efficient one-dimensional adaptive sampling design algorithm which is presented as follows.

1. For a given profile, divide the curve at inflection points, if any, into several segments that are solely concave or convex.
2. For each segment, evaluate the approximation error of the interval containing the two endpoints on the profile curve.
3. If the error is greater than a threshold that is a fraction of the initial error from step 2, an extra sampling point is inserted on the profile curve at the midpoint of the interval; Otherwise, stop;
4. For each subinterval formed by insertion of a new point, repeat steps 3 and 4 until the approximation error of each interval is smaller than a threshold value.

Applying the algorithm on several typical simulation signals, the tests are carried out (Figure 1). It is presented that the adaptive sampling allocate dense sampling points at key locations where has high curvatures. After reconstruction with linear interpolation, the root mean square error (RMSE) of the deviation from the original profile is computed using the Newton-Cotes formula in rectangle rule (N=400) (Table 1). It can be seen that except from the sinusoidal wave, adaptive sampling presents significantly lower RMS errors. Particularly for the triangle wave signal, the construction error is reduced an order of magnitude.

3 TECHNIQUE TRANSFER

To make the algorithm practical in profile measurement, an adaptive profile sampling measurement procedure is suggested for the stylus profilometer.

1. For a given sample, locate the required sampling line under the stylus of a profilometer.
2. Measure a profile using small enough sampling interval uniformly.
3. Analyze the sampled profile and design the positions of necessary adaptive sampling points using the two-dimensional adaptive sampling algorithm mentioned in Part 2.
4. Adaptively sample the profile again to obtain the data at designated locations.

Thus the information at key positions is retained while other unnecessary information is excluded out. Basically the profile adaptive sampling acts like a data compress process. It does not reduce the measuring time because it samples a profile in twice, but storage of the sampling data is reduced. This is important when measuring the micro- form of a large (greater than 10 mm) profile in structured surface measurement. However, a key problem in this adaptive sampling process is the re-positioning of the second sampling. The repositioning accuracy of the stylus would be directly transferred to the consequent sampling positions. If a large enough bias from the anticipated sampling positions is occurred, a significant reconstruction error can be produced.

A solution is suggested as follows in which the repositioning error can be ignored:

1. For a given sample, locate the required sampling line under the stylus of a profilometer.

2. Measure a profile using small enough sampling interval uniformly.
3. Analyze the sampled profile and design the positions of necessary adaptive sampling points using the two-dimensional adaptive sampling algorithm mentioned in Part 2.
4. Retain the sampled data at the designated positions analyzed at step 3 while other information is excluded.

Except from the fourth issue, the revised process is the same as the earlier process. In essence, this process has no difference from a data compression process in which only the important information in measurement is retained and others are pruned out.

4 THE SIMULATION

In this part, the proposed adaptive sampling method is tested. To make it practical, four typical structured surfaces containing bumps, triangle wave, saw-tooth and undulation curve are measured using the Talysurf PGI profilometer using $0.25 \mu\text{m}$ as the sampling spacing. Considering the existence of the repositioning uncertainty, we set a random starting point for each sampling simulation. Then, the target data are adaptively or uniformly sampled by computing simulation using differing number of the sampling points. After simulating 100 times for each test, the reconstruction error and its variations are computed. The distribution of the sampling points is shown in figure 2, and the reconstruction accuracy and repeatability is presented in figure 3.

In the simulated sampling processes for the four practical samples, the same result as described in part 2 is found. Adaptive sampling allocates dense sampling points at key locations with high curvatures. Under a predefined condition, adaptive sampling has lower reconstruction errors and uncertainties compared to the uniform sampling with the same size. It can be seen clearly from Figure 3 that adaptive sampling presents a better performance of reconstruction error both on accuracy and precision. The RMS error of adaptive sampling is usually half of the error of uniform sampling. This is understandable because generally a dense uniform sampling has a lower reconstruction error and uncertainty than a sparse uniform sampling. Therefore, the adaptive sampling which is based on an initial dense uniform sampling and the second process to retain the key information leads to a better reconstruction performance.

With increasing sampling size, the reconstruction errors of adaptive sampling and uniform sampling tend to converge. For the four samples above, when sampling points exceed 1000, the advantage of adaptive sampling becomes blurred. Therefore, if the required sampling size cannot be too large, adaptive sampling presents clearly a better performance of surface reconstruction both in accuracy and repeatability.

5 CONCLUSIONS AND THE FUTURE WORK

A profile adaptive sampling algorithm proposed by Shih et al [2] was redeveloped to two practical versions for stylus profilometers. Ignoring the potential repositioning error of the sensing stylus, the reconstruction accuracy and repeatability of the adaptive algorithms were tested on four practical structured surface samples. Compared with the uniform sampling at the same sampling size, the results show that the reconstruction accuracy and repeatability of adaptive sampling is clearly higher than uniform sampling when sampling size is not large enough. Thus it has smaller sampling uncertainties.

However, the measuring time has not been reduced in practice for the profile measurement cases. The unique advantage of this method is that the data storage is reduced when keeping the same reconstruction accuracy comparing with uniform sampling. It acts like a data compression which has been investigated in image processing.

Although the one-dimensional adaptive sampling has no advantage in reducing the measuring duration, the two-dimensional adaptive sampling (areal measurement) based on an adaptive selection of measuring cross-sections is expected to improve efficiency. The method based on the CAD model has been proposed by Shih [2] in 2008. However, in practical measurement, there are some difficulties need to be solved. The most awkward two problems are:

1. The deviations exist between the practical samples and the CAD models. If a sampling design based on the CAD model is given, the consequent measurement could miss some imperfections such as defects.
2. The positioning or repositioning error of the applied instrument always exists. Therefore, the practical sampling positions would have a bias from the anticipated positions.

The next step of the research is to implement the method on areal measurement. The advantage both on measuring time, data storage and reconstruction uncertainty is expected to be realized in that case.

6. References

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Table 1. The RMS error of uniform sampling and adaptive sampling for the typical periodic signals

Signal type	Triangle wave (42 points)	Square wave (65 points)	Sinusoidal signal (49 points)
RMSE of uniform sampling	$3.6 \times 10^{-3} \mu\text{m}^2$	$9.5 \times 10^{-3} \mu\text{m}^2$	$2.1 \times 10^{-3} \mu\text{m}^2$
RMSE of adaptive sampling	$3.2 \times 10^{-4} \mu\text{m}^2$	$5.2 \times 10^{-3} \mu\text{m}^2$	$2.2 \times 10^{-3} \mu\text{m}^2$

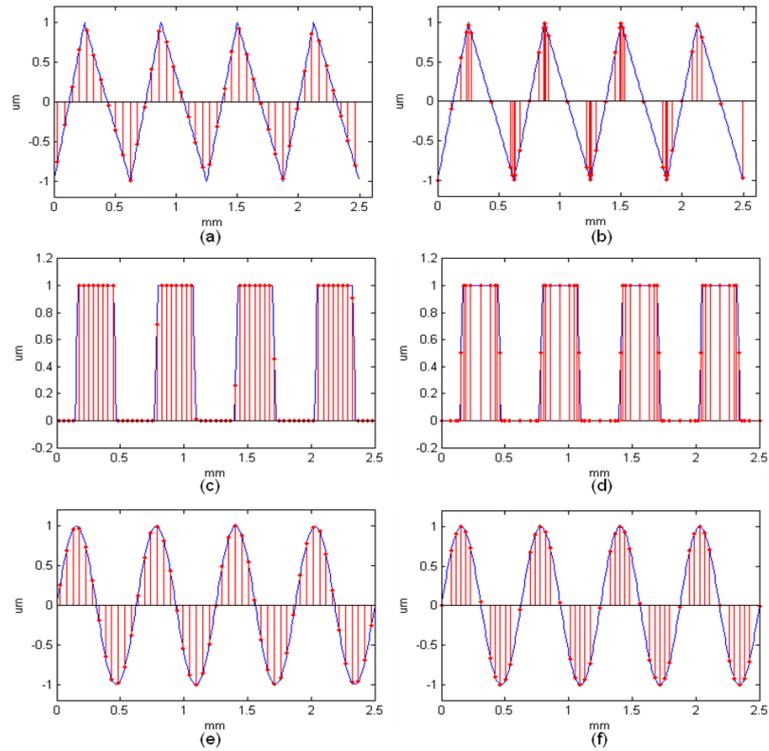


Figure 1. Comparison of uniform sampling and adaptive sampling. (a) 42 points uniform sampling and (b) 42 points adaptive sampling for triangle-wave signal; (c) 65 points uniform sampling and (d) 65 points adaptive sampling for square wave signal; (e) 49 points uniform sampling and (f) 49 points adaptive sampling for sinusoidal signal.

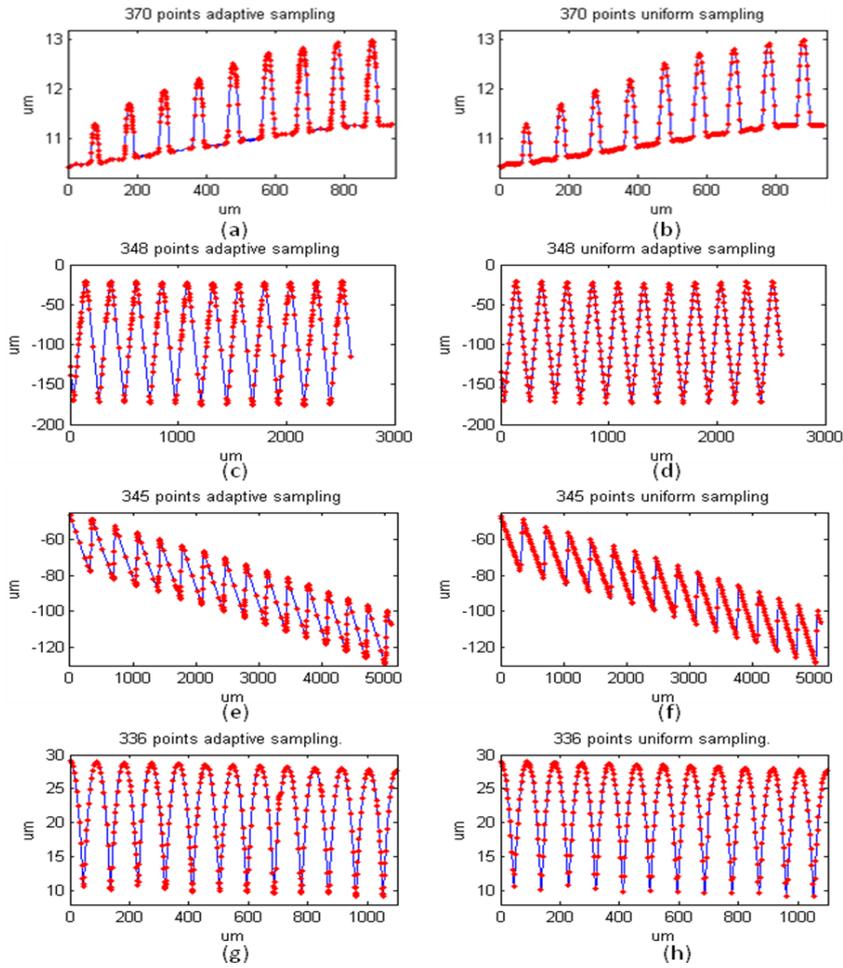


Figure 2. Comparison of adaptive sampling and uniform sampling for (a, b) bumps, (c, d) triangle wave, (e, f) saw-tooth and (g, h) undulation curve.

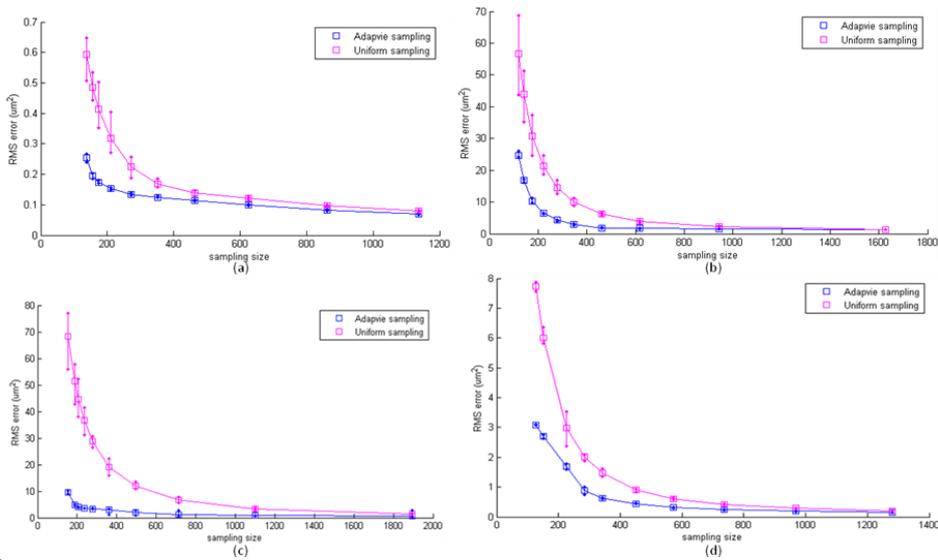


Figure 3. RMS reconstruction error and variations of adaptive sampling (blue) and uniform sampling (mauve) using different sampling sizes for practical samples (a) bumps (b) triangle wave (c) saw-tooth wave and (d) undulation wave.