A SURVEY OF POTENTIAL SAMPLING STRATEGIES FOR MEASUREMENT OF STRUCTURED SURFACES

J. Wang, X. Jiang And L. Blunt
Centre For Precision Technologies
Computing And Engineering, University Of Huddersfield, Queensgate, Huddersfield HD1 3DH, Uk

ABSTRACT

Uniform sampling is the predominant sampling method for surface measuring instruments. However, measurement for structured surfaces brings an increasingly serious conflict between sampling range and small resolution. A flexible sampling design based on sufficient previous knowledge of the surface ingredient is a potential solution. Adaptive sampling techniques are such strategies. In this paper basic specifications and drawbacks of uniform sampling schemes were issued. As potential solutions, some advanced adaptive sampling methods e.g. sequential stopping sampling, optimal model-based strategies and adaptive allocation strategies etc which were raised from computer graphics, CAD/CAM and CMM measurement are surveyed. However, transplanting of these strategies to surface metrology instruments is still questionable. Two basic questions are raised at the end.

Keywords structured surfaces, advanced adaptive sampling, uniform sampling

1 INTRODUCTION

Sampling is an inconspicuous part in surface metrology. However, measurement for structured surfaces brings an increasingly serious conflict between sampling range and small resolution which are calling for advanced sampling techniques. In statistics, there are many sampling methods: random sampling, systematic (uniform) sampling, stratified sampling, cluster sampling & multi-stage sampling, and adaptive sampling etc. For populations that are rare, unevenly distributed, hidden, or hard to reach, conventional sampling designs such as simple random sampling or uniform sampling lead to estimates with high variances and potential biases (Thompson 1997). On the contrary, with sufficient previous knowledge of the surface, sampling precision and efficiency can be improved. The adaptive sampling is such a strategy.

Sampling is the essential process in conversion from a real continuous surface to its discrete digital form; the sampling should allow finite point data to reconstruct the original continuous surface with no or little infidelity. But different from a conventional time signal, a space signal is probably a multivalued function of space distance which indicates its discontinuity or re-entrance (Figure 1). In surface metrology, the sampling scheme or strategy require a wide degree of flexibility in estimating parameters as well. Structured surfaces (Evans and Bryan 1999) are the surfaces with a deterministic pattern of usually high aspect ratio with geometric features designed to give a specific function. Unevenness of the surface integrity is the typical property of a structured surface.

Sampling for a surface is an interesting topic that can be traced back to 1970s. Influence and feasibility of different sampling grids and sampling conditions (e.g. sampling interval, sampling size and sampling area) for stochastic surface were argued (Tsukada and Sasajima 1982; Lin, Stout et al. 1991; Stout, Sullivan et al. 1993). From 1990s, freeform surfaces (e.g. vehicle exterior shape) raised. Uniform sampling asks for huge data storage and long time of process. And the interpolation errors in complex regions are remarkable. Novel sampling techniques of coordinate machine (CMM) measurement were investigated (Elkott, Elmaraghy et al. 2002; Hu, Li et al. 2004). The advanced sampling design based previous knowledge of the surface ingredient exhibited its flexibility and efficiency. In this century, with the development of structured surfaces, conventional surface measurement instruments like stylus, interferometers, SPMs, etc are employed for inspection. However, the similar problem as in freeform measurement is encountered. Large sampling range and small resolution for key areas like edges, steps are in need. Conflict between sampling accuracy and sampling range is prominent.
Adaptive sampling is a new sampling design that can redirect sampling effort during a survey in response to the observed values (Thompson, Seber et al. 1996). In surface measurement, the observed values (or the previous knowledge) can be a preliminary measurement or its CAD models. In the past, advanced adaptive sampling techniques were developed in which systematic design, stratification or cluster process etc was combined. They include optimal model-based strategies, sequential stopping methods, adaptive allocation design, etc. This paper is set down to survey the potential sampling techniques currently developed in surface instruments and other fields like CMM measurement, CAD/CAM and computer graphics etc, by

which novel sampling methods could be inspired for structured surface measurement. Disadvantages of uniform sampling and advantages of adaptive sampling were issued.

2 UNIFORM SAMPLING SCHEMES

Uniform sampling is the dominant sampling strategy in surface metrology which is utilized in almost all the available instruments. Uniform sampling, or referred to as systematic sampling, relies on arranging the target population according to some ordering scheme and then selecting elements at regular intervals through that ordered list. All 'units' in the population have the same probability of selection thus it is a type of "equal probability sampling" (Wikipedia 2009).

In Whitehouse's work in 1980s, mathematical rationality of uniform sampling by 3-points (for one-dimensional sampling, , 4-points, 5-points, and 7-points schemes (Figure 2) were analyzed (Whitehouse and Phillips 1985; Li, Phillips et al. 1989). The advantage of using hexagonal sampling scheme (7-points) is less consuming of computational time. And It was pointed that theoretically the 7-points sampling scheme is a more robust digital procedure by Nayak's equations (Nayak 1971), because this scheme is closer to the real continuous situation in mathematical calculation of summits density, etc. However, It was pointed by Preston (Preston, Duff et al. 1979) that there is a reluctance in using anything other than a rectangular sampling scheme (5-points) because it is perceptually more satisfactory for humans to observe straight vertical features on a square grid pattern. Transformation of the rectangular grid (5-points) from 1D to 2D is more natural. A usual example is that of the fast Fourier transform (FFT). It is very simple to progress from a 1D FFT to a 2D FFT simply by taking all the rows in turn and then the columns. Thus it is understandable why the 5-points grid sampling scheme is the popular approach currently. All the current 3D instruments use this method (Stout, Blunt et al. 2000).

Unfortunately, uniform sampling is proved inefficient if both high precision and large range are required, especially when the high precision is locally specified. Considering a structured surface (e.g. a micro-fluidic surface) which has a 100mm sample range and 10um slope width in a groove, a full precision uniform sampling would call for unacceptable mass data storage and acquisition time. And interpolation errors in complex area would be remarkable. Smart sampling methods are in need.

3 ADVANCED ADAPTIVE SAMPLING METHODS

With sufficient previous knowledge of the surface, sampling precision and efficiency can be improved. The adaptive sampling is such a strategy. Plenty of advanced sampling strategies have been proposed in the past, especially in the last 20 years. Systematic design, stratification and adaptive sampling etc were combined that some advanced adaptive sampling methods were developed. These advanced techniques are classified into three types: optimal model-based strategies, sequential stopping sampling and adaptive allocation (or named as adaptive stratified sampling). Different advanced sampling methods derive from different application areas, like visual optimization, engineering measurement, and environment (ocean, atmosphere, electromagnetic waves, etc) inspection. A primary survey on the advanced sampling techniques is elaborated as below, and examples are listed in Table 1.

3.1 OPTIMAL MODEL−BASED SAMPLING

In CAD/CAM, geometric modeling, and computer vision techniques, adaptive sampling was introduced first for obtaining an effective sampling size and reconstruction accuracy. And some of them were proposed mainly for perfect visual or measuring representation. Many scientists from different fields contributed here. Two branches – iterative algorithm and features stratification algorithm – compose the category.

The iterative method generally obey the following strategy (de Figueiredo 1995):

1. Choose a criterion for refining samples;
2. Evaluate the criterion on the interval;
3. If the curve is almost flat in the interval, the sample is given by its two extremes;
4. Otherwise, divide the interval into parts and recursively sample the two parts.

As for the feature stratification algorithm, specific surface feature (e.g. surface curvature, gradient, depth, intensity, etc) in each quadrant were ranked. And the sampling grids or points were allocated according to the ranking of the surface feature(s). Its algorithm is simple than the iterative method, while the control of presentation accuracy isn't easy.

Many examples in computer graphics(Terzopoulos and Vasilescu 1991; Li 1995) and CMM measurement (Cho and Kim 1995; ElKott and Veldhuis 2005) were listed in the Table 1. An typical optimal model based sampling was inspired by the 'spring-mass system'(Terzopoulos and Vasilescu 1991). Like a level system as illustrated in Figure 3 (left), that the heavier weight M1 shares the shorter part of the level, and vice versa. An iterative algorithm by calculating the spring tension, resistance and the speed, acceleration of each mass and spring were implemented until the system become stable. Thus the area with high mean curvature or other feature attributes was sampled densely. Figure 3 (middle & right) Adaptive sampling in visual process (illustrated a sample of adaptive sampling strategy which is based on the cross 'mass-spring system'.

If the CAD model of a given surface is known in advance, an optimal adaptive sampling design can be extracted. However, the theoretically optimal strategies are not necessarily the most practical because they may require an unattainable amount of previous information about the population and tend to be computationally and implementationally complex (Solomon and Zacks 1970).

3.2 SEQUENTIAL STOPPING SAMPLING

Most of the time in surface measurement the CAD model is unknown in advance. An adaptive method named as sequential stopping sampling was paralleling. With sequential stopping sampling, sampling continues sequentially until a given criterion, based for example on observed incidence or sample variance, is attained. In sequential sampling instruments like stylus, scanning probe microscopes (SPMs) and CMMs, the adaptive sampling method is promising.

An typical example was the equal arc-length sequential adaptive sampling strategy which was proposed by Hu et al (Hu, Li et al. 2004). By this method, tangent in each sampling sequential sampling point of a cubic spline curve is extrapolated. Step-length was adjusted adaptively according to the slope variation of the sample curve with arc-length maintained to be constant. Thus the small slope region is sampled sparsely while the large slope region is sampled densely. Figure 4 illustrated the algorithm.

3.3 ADAPTIVE ALLOCATION

As for surface interferometers (e.g. the coherence correlation interferometer), surface sampling is not sequential. Considering a multi-scale measurement, lens switching would be a solution inevitably. The adaptive allocation sampling design (adaptive stratified sampling) would be a promising solution. With adaptive allocation designs, an initial stratified sample is selected. Based on the observed values for the initially selected units, an additional stratified sample is selected with allocation of sample sizes to strata based on the initial observations. For example, a given surface is initially measured and stratified. Additional samplings are implemented in each interesting regions with allocation of proper sample size to the strata.

A typical example named as hypercube stratified 'smart' sampling is inspired by adaptive sampling for wireless sensor network proposed by Willett et al (Willett, Martin et al. 2004; Castro, Haupt et al. 2006). Three steps comprised the 'smart' sampling technique (Figure 5):

1. Preliminarily (coarsely) sampling uniformly over the domain of function;
2. Recursively divide the domain into hypercubes, and prune to adapt to the data
    a) Divide the original area into hypercube;
    b) Curvature detect of the curvatures of sub-areas with a specific threshold;
    c) If the curvature exceeds the threshold, return to the step (a) unless an acceptable size is obtained;
3. Uniformly sampling (finely) in each cell of pruned partition to form final estimate.

The smart sampling method is an effective approach that can be used in non-raster scanning measurement e.g. vertical scanning interferometers (VSI) etc.

4 SUMMARIES

Different structured surfaces (e.g. rotational symmetric patterns, tessellations) and stochastic surfaces ask for different sampling specifications. 5-points uniform sampling scheme is the dominant sampling methods in current surface instruments. However it is proved inefficient if both high precision and large range are required, especially when the high precision is locally specified.

Basically the optimal model-based sampling is useful when the CAD model of the given surface is known in advance. Algorithms for extracting an adaptive sampling mesh would be complex and time consuming. And some of the methods (e.g. visual sampling as in Figure 3) are difficult to be used in surface instruments because of the sampling mechanism (e.g. raster scanning). The sequential CMM measurement based methods could be utilized in stylus instruments and SPM etc, while the adaptive allocation strategy could be utilized in surface interferometers. If the adaptive sampling techniques are adopted, however, many technical details are questionable and have to be confirmed in the future. Two basic questions are firstly raised:

1. Multi-scaling of sampling points is the inevitable result of adaptive sampling methods. Then how to do data fusion (fusion of different measuring references, data structure and presentation, etc) of multi-scale sampling points?
2. How to do numerical process (e.g. numerical convolution, Fourier transform, etc) of multi-scale data F(x) of a profile/surface with a specific filtering function G(x) in Figure 6.

5 REFERENCES

Ainsworth, I., M. Ristic, et al. (2000). "CAD-Based Measurement Path Planning for Free-Form Shapes Using Contact Probes." The International Journal of Advanced Manufacturing Technology **16**(1): 23-31.

Castro, R., J. Haupt, et al. (2006). Compressed Sensing Vs. Active Learning. Acoustics, Speech and Signal Processing, 2006. ICASSP 2006 Proceedings. 2006 IEEE International Conference on.

Cho, M. W. and K. Kim (1995). "New inspection planning strategy for sculptured surfaces using coordinate measuring machine." International Journal of Production Research **33**(2): 427-427.

de Figueiredo, L. H. (1995). "Adaptive sampling of parametric curves." Graphics Gems V: 173–178-173–178.

Edgeworth, R. and R. G. Wilhelm (1999). "Adaptive sampling for coordinate metrology." Precision Engineering **23**(3): 144-154.

Elkott, D. F., H. A. Elmaraghy, et al. (2002). "Automatic sampling for CMM inspection planning of free-form surfaces." International Journal of Production Research **40**(11): 2653 - 2676.

ElKott, D. F. and S. C. Veldhuis (2005). "Isoparametric line sampling for the inspection planning of sculptured surfaces." Computer-Aided Design **37**(2): 189-200.

Evans, C. J. and J. B. Bryan (1999). ""Structured", "Textured" or "Engineered" Surfaces." CIRP Annals - Manufacturing Technology **48**(2): 541-556.

Hu, J., Y. Li, et al. (2004). "Adaptive sampling method for laser measuring free-form surface." The International Journal of Advanced Manufacturing Technology **24**(11): 886-890.

Li, M., M. J. Phillips, et al. (1989). "Extension of two-dimensional sampling theory." Journal of Physics A: Mathematical and General **22**(23): 5053-5063.

Li, S. Z. (1995). "Adaptive Sampling and Mesh Generation." COMPUTER AIDED DESIGN **27**: 235--240-235--240.

Lin, T. Y., K. J. Stout, et al. (1991). Determination of proper sampling spacing for 3-D topography measurement of machined surfaces using power spectral analysis. Proceedings of 7th America Society of Precision Engineering.

Nayak, P. R. (1971). "Random process model of rough surfaces." ASME J. Lubr. Technol **93**(3): 398–407-398–407.

Preston, K., M. J. B. Duff, et al. (1979). "Basics of cellular logic with some applications in medical image processing." Proceedings of the IEEE **67**(5): 826-856.

Solomon, H. and S. Zacks (1970). "Optimal Design of Sampling from Finite Populations: A Critical Review and Indication of New Research Areas." Journal of the American Statistical Association **65**(330): 653-677.

Stout, K., P. J. Sullivan, et al. (1993). Development of Methods for the Characterisation of Roughness in Three Dimensions, University of Birmingham.

Stout, K. J., L. Blunt, et al. (2000). Development of methods for the characterisation of roughness in three dimensions, Penton Press.

Terzopoulos, D. and M. Vasilescu (1991). Sampling and reconstruction with adaptive meshes. Computer Vision and Pattern Recognition, 1991. Proceedings CVPR '91., IEEE Computer Society Conference on.

Thompson, S. K. (1997). "Adaptive sampling in behavioral surveys." NIDA Research Monograph **167**: 296-319.

Thompson, S. K., G. A. F. Seber, et al. (1996). Adaptive sampling, Wiley New York.

Tsukada, T. and K. Sasajima (1982). "An optimum sampling interval for digitizing surface asperity profiles." Wear **83**(1): 119-128.

Whitehouse, D. J. and M. J. Phillips (1985). "Sampling in a two-dimensional plane." Journal of Physics A: Mathematical and General **18**(13): 2465-2477.

Wikipedia. (2009). "Sampling (statistics)." from http://en.wikipedia.org/wiki/Sampling_(statistics).

Willett, R., A. Martin, et al. (2004). Backcasting: adaptive sampling for sensor networks. Proceedings of the 3rd international symposium on Information processing in sensor networks, Berkeley, California, USA, ACM.

Classification	Application areas	Examples

Optimal model-based sampling	Visual sampling, CAD/CAM	1. Iterative adaptive mesh sampling based on 'mass-spring system' (Terzopoulos and Vasilescu 1991) 2. Iterative adaptive mesh sampling based on surface curvedness (Li 1995)
	CMM measurement	1. Multiscale adaptive grid sampling based on two stage local curvature detect (Cho and Kim 1995) 2. Iterative adaptive sampling for NURBS CAD model based on iso-parametric curve (Ainsworth, Ristic et al. 2000) 3. Adaptive sampling for NURBS CAD model based on patch size or Gaussian curvedness, etc (Elkott, Elmaraghy et al. 2002) 4. Iterative adaptive sampling based on NURBS CAD model and deviation function or mean curvature change (ElKott and Veldhuis 2005)
Sequential stopping sampling	CMM measurement	1. Iterative adaptive sampling based on CAD & preliminary normal measurement and 'error space' interpolation (Edgeworth and Wilhelm 1999) 2. Equal arc-length sequential adaptive sampling based on previous measurement and curve tangent extrapolation (Hu, Li et al. 2004)
Adaptive allocation	Wireless sensor network	Multiscale adaptive grid sampling based two/multi stage feature dectect for clustering (Willett, Martin et al. 2004; Castro, Haupt et al. 2006)

Table 1 Adaptive sampling strategies applied in different areas

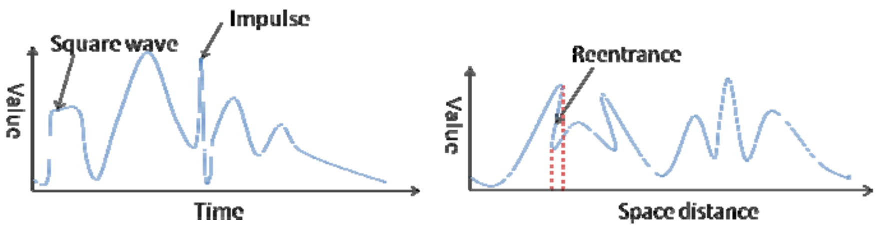

Figure 1 Difference between real time signal and space signal

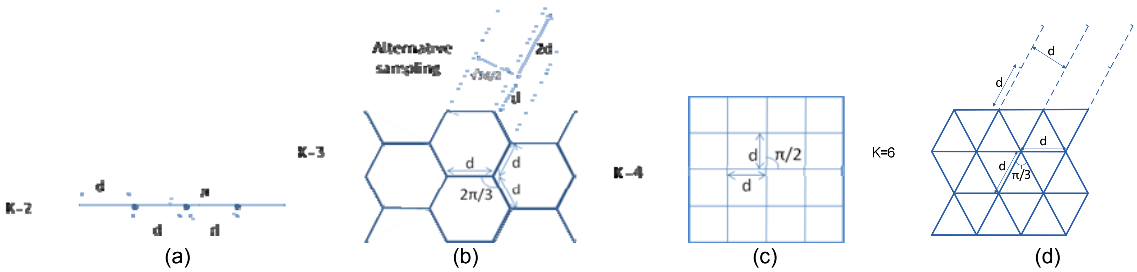

Figure 2 three-points, four-points, five-points and seven-points uniform sampling schemes illustration (Whitehouse and Phillips 1985)

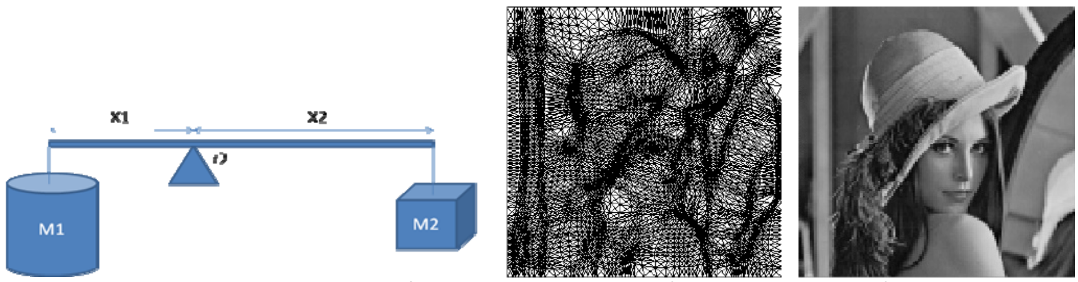

Figure 3 Adaptive sampling in visual process (left) the level system (middle & right) original image &adaptive sampling mesh (Terzopoulos and Vasilescu 1991)

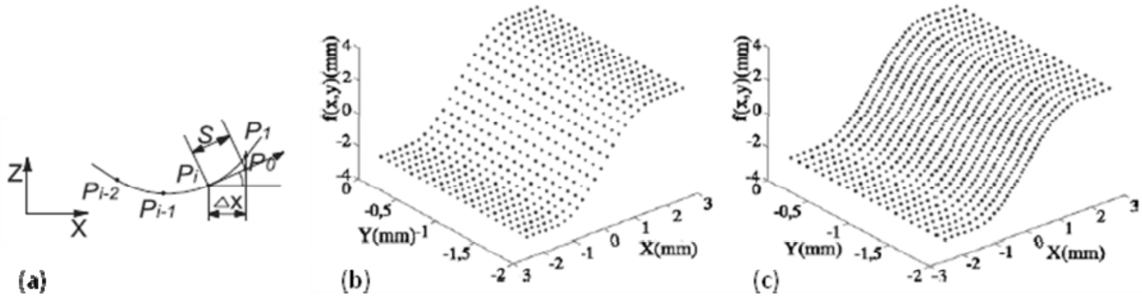

Figure 4 Equal arc length sampling (a) extrapolation of arc length S and the step length Δx from the sequential sampling points Pi-2, Pi-1, and Pi (b) a uniform sampling mesh (c) the equal arc length sampling mesh (Hu, Li et al. 2004)

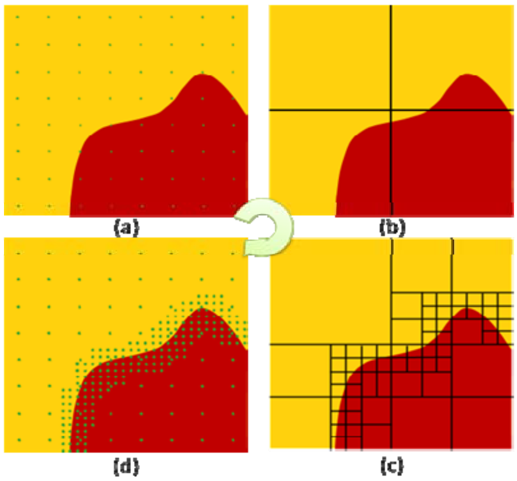

Figure 5 Illustration of the hypercube stratified 'smart' sampling (a) uniform initial sampling; (b) and (c) behaving the recursively dividing process for hypercubes generation; (d) represent of the final sampling points

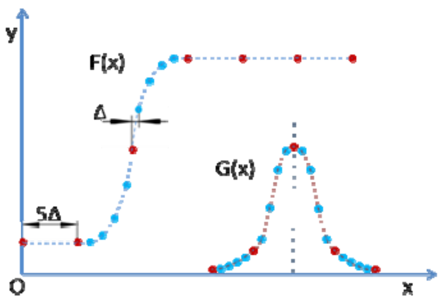

Figure 6 Two (multi)− scale signal F(x) and the convolution function G(x) (the red dots are larger scaled sampling points, while the blue dots are finer scaled sampling points)