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Generation of 3D random topography datasets with periodic boundaries for surface metrology algorithms and measurement standards

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ABSTRACT

A procedure is presented to generate three-dimensional (3D) random topography datasets with periodic boundaries for the evaluation of surface metrology algorithms and original data for measurement standards. A non-causal two-dimensional (2D) autoregressive (AR) model, which expresses the surface as a linear weighted summation of AR parameters and topography data in addition to a random noise component, is applied to computationally generate 3D random topography data. By the use of an extension that assumes periodic boundaries, the edges of the generated data become continuous across the boundaries. It has been verified that the spectral properties are not affected by this extension. This technique offers advantages for the evaluation of computational techniques for surface metrology, such as filtrations and spectral analysis since the edge effect can be avoided by assuming periodic boundaries, and inherent effects of the techniques can be evaluated. In addition, for use as a random measurement standard for instrument calibration, it is possible to simply arrange the generated data repeatedly in the measuring window similarly to floor tiles without introducing discontinuous edges at the boundaries of the data.

1. Introduction

Recently, surface texturing has attracted the attention of tribologists since it can be used to dramatically improve friction and wear without changing the materials and the lubricants [1–3]. Thus, the importance of the evaluation techniques of surface texture, including measurement and analysis, is growing, especially in regard to areal three-dimensional (3D) textures. To ensure accuracy of the measuring instruments, standard specimens are required. All the instruments should be verified according to the international standard to allow comparisons [4]. In addition, reference datasets (softgauges) are needed to check the correctness of evaluation algorithms. Softgauges as well as reference algorithms are described in ISO 5436-2 [5].

For linear two-dimensional (2D) surface texture-measuring instruments, calibration standards have been established and are now available [6]. In addition, Blunt et al. developed softgauges for line profiles [7]. Bui and Vorburger proposed an Internet-based surface texture analysis system for algorithm verification [8,9]. However, areal calibration standards and softgauges have not as yet been established.

The reference data would be required following properties [10].

(1) Reference data should be generated by a defined logic.
(2) Reference data should have expected values of geometric and statistic quantity.
(3) The logic should be capable of changing conditions such as data size and intervals.

Moreover, softgauges should include randomness since topographical data extracted by measuring instruments has randomness more or less.

To fulfil these requirements, data generation techniques based on statistical modelling are applicable. Patir [11], Bakolas [12] and Manesh et al. [13] developed such a technique by using the 2D moving average (MA) model. Whitehouse [14] and Xingian and Yiyun [15] proposed the causal 2D autoregressive (AR) model. Hu and Tonder [16] applied the 2D finite impulse response (FIR) filter to generate random 3D topographical data. Wu [17,18] and Pawlus [19] studied the data generation by using FFT. The authors studied a non-causal 2D AR model for the generation of datasets and found that the resulting model is superior to a causal model in terms of spectral properties [20].

In this paper, to establish a more convenient data generation procedure, the concept of a periodic boundary is introduced into the non-causal 2D AR model.

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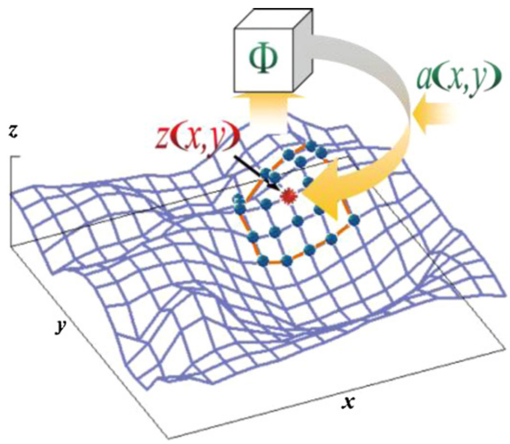

Fig. 1. Schematic diagram of the non-causal 2D AR model.

2. Mathematical background and computational techniques

2.1. Definition of non-causal 2D AR model

When the values of the ordinate height $z(x, y)$ $\{x=0, 1, \ldots, X_n-1, y=0, 1, \ldots, Y_n-1\}$ of the areal surface are assumed to be random variables measured from the overall mean value, the non-causal 2D AR model for $z(x, y)$ is given as follows (see Fig. 1) [20].

$$z(x, y) = \sum_{(i,j)}\sum_{\in D}\phi(i, j)z(x-i, y-j) + a(x, y) \tag{1}$$

$$D = \{(i, j)|(-m \le i \le m, -n \le j \le n), (i, j) \ne (0, 0)\} \tag{2}$$

where $\phi(i, j)$ is the AR parameter, $a(x, y)$ represents random input, i and j are integers, D is the region of regression and m and n denote the order of the regression in the x and y direction, respectively. Note that x and y are data numbers, not the coordinate values, for simplification of equations below. The coordinate values are given by multiplying data intervals, Δx and Δy, respectively. Let us denote the matrix $\{\phi(i, j)\}$ as Φ. The regression is expressed by a liner-weight summation with the Φ and height in the region defined by D. It should be noted that D does not have to large enough to cover the whole wavelength to be included in $\{z(x, y)\}$. This model is an extension of the causal AR model in terms of the region of regression. A comparison between the causal and the non-causal model is illustrated in Fig. 2. In the case of the causal model, a certain order (i.e. directionality) of x and y is assumed (Fig. 2(a)). This unnatural directionality is excluded in the non-causal model (Fig. 2(b)). By this extension, the estimation of Φ becomes a non-

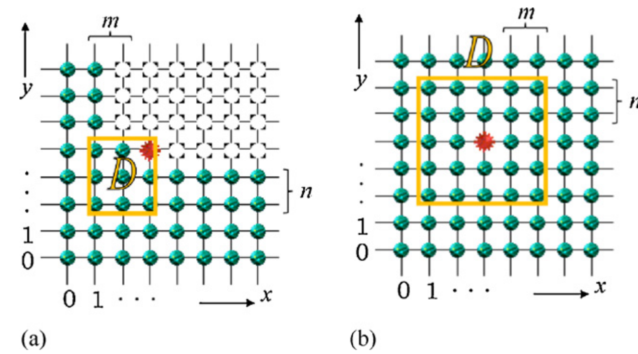

Fig. 2. Differences in the region of regression between the causal (a) and the non-causal (b) 2D AR model.

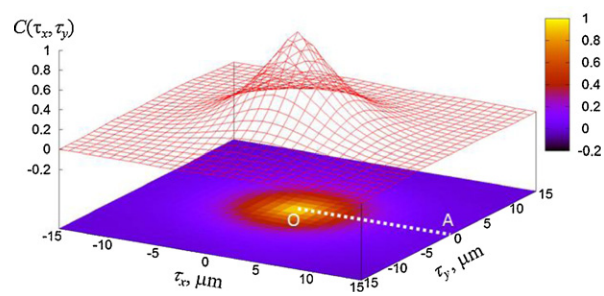

Fig. 3. Example of ACC as defined in Eq. (3).

linear problem and the generation of $\{z(x, y)\}$ involves the solution of simultaneous equations [20]. Procedures of estimation and generation are detailed in Appendices A and B, respectively.

2.2. Specification parameters

The spectral properties of Eq. (1) can be specified by using the following autocorrelation coefficient (ACC) $C(\tau_x, \tau_y)$

$$C(\tau_x, \tau_y) = \exp\left[-\left\{\left(\frac{\tau_x}{\beta_x}\right)^2 + \left(\frac{\tau_y}{\beta_y}\right)^2\right\}^{\omega}\right] \tag{3}$$

where τ_x and τ_y are the lags and β_x and β_y are the correlation distances in the x and y direction, respectively, and ω is the power index. As shown in Fig. 3, the ACC as defined in Eq. (3) has a value of unity at the origin ((τ_x, τ_y)=(0, 0), denoted as O in Fig. 3) and decays with an increase in τ_x and τ_y.

To clarify meaning of the various parameters, the cross-section of the ACC in the direction of τ_x (denoted as OA in Fig. 3) is shown in

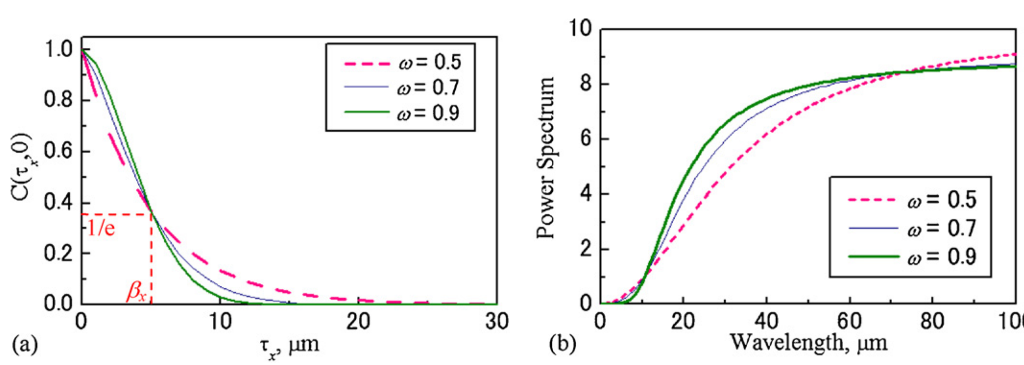

Fig. 4. Effect of the power index ω on ACC (a) and the respective power spectra (b) ($\beta_x = 5$ μm).