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Data fusion for accurate microscopic rough surface metrology

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ABSTRACT

Data fusion for rough surface measurement and evaluation was analyzed on simulated datasets, one with higher density (HD) but lower accuracy and the other with lower density (LD) but higher accuracy. Experimental verifications were then performed on laser scanning microscopy (LSM) and atomic force microscopy (AFM) characterizations of surface areal roughness artifacts. The results demonstrated that the fusion based on Gaussian process models is effective and robust under different measurement biases and noise strengths. All the amplitude, height distribution, and spatial characteristics of the original sample structure can be precisely recovered, with better metrological performance than any individual measurements. As for the influencing factors, the HD noise has a relatively weaker effect as compared with the LD noise. Furthermore, to enable an accurate fusion, the ratio of LD sampling interval to surface autocorrelation length should be smaller than a critical threshold. In general, data fusion is capable of enhancing the nanometrology of rough surfaces by combining efficient LSM measurement and down-sampled fast AFM scan. The accuracy, resolution, spatial coverage and efficiency can all be significantly improved. It is thus expected to have potential applications in development of hybrid microscopy and in surface metrology.

1. Introduction

Microscopic rough surface structures are directly related with various physic-chemical behaviours such as friction, wetting, lubrication and wear [1]. To establish internal relationships between functional performances and roughness parameters and then optimize surface textures to enable better usages, quantitative characterization of surface roughness at the micro- and nano-scale is of fundamental importance. Many techniques have been available for surface dimensional nanometrology. Among them, atomic force microscopy (AFM), laser scanning microscopy (LSM) and scanning electron microscopy (SEM) are probably the most popular ones. Calibrated AFM can measure the surface topography of almost all kinds of specimens with even sub-nanometer resolution [2]. Despite that, the raster scan of the probe or the sample stage together with the scanner resonance restrict the data acquisition efficiency [3]. The scan rate of conventional AFM is usually within several hertz. Conversely, optical methods such as LSM and light interference are much more efficient and can easily reach a larger inspection area. However, the lateral resolution is not as good as AFM because of the diffraction barrier. In addition, optical bias will lead to large amounts of image artifacts, which are relevant to local slope, materials and multiple scattering [4]. These characteristics cause quantitative evaluation rather difficult. SEM measurement has sufficiently high resolution but requires the coating of a thin metal film for a non-conductive specimen, which may induce unwanted changes of the surface structures. Furthermore, roughness evaluation from SEM data needs intricate three-dimensional (3D) reconstruction procedures [5].

As a result, practical situations that one individual technique cannot meet all the characterization requirements will be frequently encountered. To elucidate a more comprehensive surface evaluation, development of hybrid systems, which integrate two or more microscopes, has emerged as a general trend [6]. Because of the small dimensions of the sensing probe, AFM can be conveniently combined with other microscopes [7]. Several such investigations have already been advanced to exploit the integrations of AFM and kinds of optical microscopes [8]. The data acquisition by hybrid microscopy can be generally divided into two categories. In the first category, different information is obtained by different sensing methods. For instance, AFM was integrated with stimulated emission depletion microscopy to characterize topography, elastic and optical contrasts within one fixture of the specimen [9]. In these applications, measured images were simply applied with registration and subsequent overlay for apparent correlation of different measurands [10]. In the other category, the same geometrical information is acquired by all the sensing components. Such hybrid measurements are of special interest in surface dimensional nanometrology. As a typical integration, AFM was combined with white light interference to provide long-range global characterizations and high resolution local measurements

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[11]. Usually, the hybrid microscope was operated by first carrying out a rough examination of the entire area with the optical method, then followed by a detailed analysis of the region of interest with AFM [12].

To maximize the capability of an integrated system, multiple datasets from all the sensing components are required to be merged into a single one, which is expected to have a better overview of the surface structures. Multi-sensor data fusion is a well developed yet rapidly expanding approach to meet such a challenge [13]. However, data fusion for metrological application is still a newly emerged research area [14]. In literature, many previous works focused on image stitching to improve the spatial coverage, and the fusion of multi-focus images was also well established to realize a single all-focus image [15]. These investigations mainly addressed the fusion of cooperative datasets from a single instrument but different operation conditions [13]. In the case of an integrated hybrid microscope, datasets with different resolutions and coordinate systems will be involved. Fusing two-resolution metrological data is considerably more complicated. For a better inspection of the geometric quality, Xia et al. proposed a Bayesian hierarchical model for processing two datasets from coordinate measuring machines with a mechanical probe and an optical probe, respectively [16]. Similarly, optical measurements of critical dimensions with the assistance of AFM were demonstrated to have smaller uncertainties via data fusion [17]. Ramasamy and Raja compared several weight-based fusion methods on optical images of structured surfaces [18]. Recently, Colosimo et al. constructed the Gaussian process (GP) based data fusion framework for dimensional and geometric verification [19]. This non-parametric approach was validated to be quite effective and promising. Despite these preliminary progresses, the possibility of data fusion for better irregular rough surface measurements remains unclear where the structures are much more complex.

Here, we explore the feasibility of data fusion for improving rough surface evaluations by fully combining topographic datasets acquired on the same surface with different microscopes. A general situation is considered that the datasets are respectively of a higher density (HD) but lower accuracy type and a lower density (LD) but higher accuracy type. Such data features are commonly encountered in practical hybrid microscopy, for example, which integrates the optical detection and the AFM measurement. First, influencing factors including the noise strengths of HD and LD datasets, and the LD sampling interval were analyzed on numerically generated datasets. Then, experimental verifications were carried out to ascertain the fusion performances. For demonstration, surface areal roughness artifacts with specified statistical properties and roughness parameters were designed and fabricated by means of focused ion beam (FIB) technique [20]. After AFM and LSM characterizations of the artifacts, data fusion was applied on the down-sampled AFM image and the original LSM image, which respectively serve as the LD dataset and the HD dataset.

2. Methods

2.1. Rough surface generation

One-dimensional (1D) profiles and two-dimensional (2D) surfaces with specified roughness characteristics were generated first. The 1D profiles were adopted for investigating the influencing factors and evaluating the fusion performances without loss of generality. The 2D surfaces were used as design templates for FIB fabrications of roughness artifacts and subsequent LSM and AFM characterizations.

In general, the most important roughness properties of a certain profile or a surface are the autocorrelation function (ACF) and the height distribution [21]. Here, the ACF is assumed in the form of exponential decay,

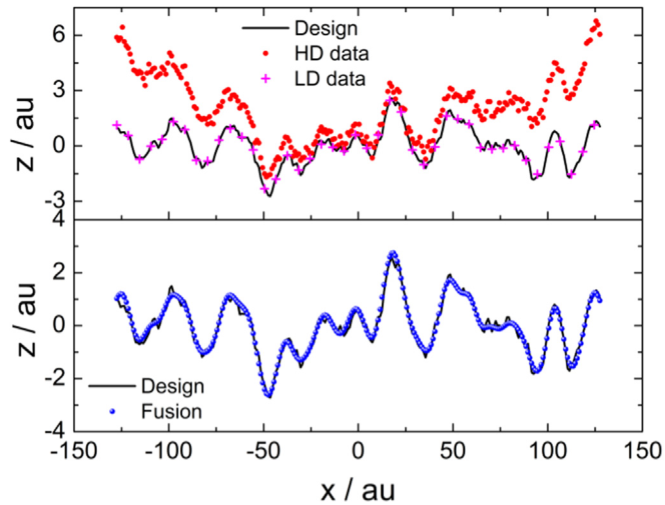

Fig. 1. Typical designed rough profile, simulated HD and LD datasets and fused profile.

$$c_p(x) = \sigma_p{}^2 \exp\left(-\frac{x^2}{\tau_x^2}\right) \tag{1}$$

In the above equation, c_p denotes the ACF of the rough profile. τ_x is the autocorrelation length defined at the $1/e$ decay and σ_p is the standard deviation of the profile heights. Similarly, the ACF of a 2D rough surface is expressed as,

$$c_s(x, y) = \sigma_s{}^2 \exp\left\{-\left[\left(\frac{x}{\tau_x}\right)^2 + \left(\frac{y}{\tau_y}\right)^2\right]\right\} \tag{2}$$

where c_s represents the ACF of the rough surface. τ_x and τ_y are respectively the autocorrelation lengths in x-and y-directions. σ_s is the standard deviation of the surface heights.

To control the height distributions, parameters such as the mean, standard deviation, skewness and kurtosis were adopted. Rough profiles or surfaces satisfying above ACFs and these pre-assigned statistical quantities were numerically generated using FFT method [21]. However, the statistical parameters of the simulated rough profiles or surfaces may deviate from the expected values. For the purpose of improving the accuracy, genetic algorithms were incorporated into the design [22].

2.2. Simulation of measurement datasets

In practical microscopy, the acquired data consist of three major components including the true topography, the measurement bias and the random noise. For clarity, we start with the case of 1D rough profiles. Mathematically, the measured topography is described by,

$$z(x) = \hat{z}(x) + \alpha x^2 + \beta\varepsilon_0 + \gamma \tag{3}$$

where the first term $\hat{z}(x)$ is the true topography designed with specified roughness parameters. The second term αx^2 is adopted to simulate the measurement bias, which is spatially correlated. Because x is defined in a range centered at 0 here, with this expression, we simply assume that the measurement is relatively accurate at the central region whereas larger deviations appear at the edges. Certainly, other forms can also be applied without any