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Continuous separating method for characterizing and reconstructing bi-Gaussian stratified surfaces

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ABSTRACT

Existing segmented separation method for differentiating the components contained within a bi-Gaussian stratified surface has two drawbacks: 1) assumption of probability material ratio curve consisting of two lines with a knee-point rather than a smooth transition region, violates the unity-area demand on probability density function (PDF); 2) preference for large roughness-scale part, yields the message loss of small roughness-scale part. In the present study, surface combination theory is proposed to develop a continuous separation method. The two separation methods are applied for analyzing and reconstructing simulated bi-Gaussian and experimental worn surfaces. The results show that the continuous method has greatly overcome the two drawbacks and almost leads to the same surface parameters as the measured surface in the surface reconstruction.

1. Introduction

Surface texture can be considered as the fingerprint of a component or active surface [1]. Namely, the surface texture not only represents the manufacture process consequence, but also the current state of the component or part. Therefore, it is imperative to search a number of surface parameters to capture surface characteristics as far as possible. Furthermore, surface texture acts as the initial input of analyzing tribological behavior such as lubrication, contact and wear. The input data can be obtained either from measurements or numerical surface simulations. Due to its flexibility, efficiency and stability, the numerical surface reconstruction is a good alternative.

In the aspect of characterizing rough surface, the widely used central moment parameter set such as *Ra*, *Rq* ($=\sigma$), *Sk* and *Ku* works well for the surfaces generated by one process. However, it fails to assess a bi-Gaussian stratified surface which is a combination of the surface textures due to two processes. Cylinder liner of internal combustion engines manufactured by plateau honing operation is a representative bi-Gaussian surface consisting of smooth wear-resistant and load-bearing plateau with intersecting deep valleys working as oil reservoirs and debris traps. Besides two-process surfaces, any prepared surface texture is often rapidly altered by wear, also leading to a bi-Gaussian surface with a large-scale roughness in the valleys and a small-scale roughness in the plateaus left by a truncation of the peaks of the initial large-scale roughness. Generally speaking, for the two-process or worn bi-Gaussian surfaces, two main characterizing methods have been developed based on material ratio curve, i.e., Abbott curve [2]. The first one is the *Rk* parameter set (Fig. 1(a)) according to German standards DIN 4776 [3]. Its kernel is based on the use of a minimum slope line, spanning a 40% material ratio, to obtain the core roughness depth *Rk*. Since *Rk* is defined as the width of core band of roughness, the roughness above and below this band are characterized by the reduced peak height *Rpk* and reduced valley depth *Rvk* respectively, where *Rpk* gives information on the running-in period and *Rvk* embodies the lubricant storage capacity. Material ratios Mr_1 and Mr_2 are the transition points from 'peak' to 'core' and from 'core' to 'valley'. However, the *Rk* method implies a three-stratum concept for the surface, conflicting with a two-stage manufacturing process. Therefore, the probability material ratio curve provides the second choice. With this approach, the material ratio curve of a Gaussian distributed surface is a straight line when plotted on a Gaussian standard deviation scale [4] (the detailed transformation from material ratio curve to probability material ratio curve is provided in Appendix C). The intercept is the mean value of asperity height and the slope is *Rq*. Therefore, a bi-Gaussian stratified surface should exhibit two linear regions (Fig. 1b), where *Rpq* ($=\sigma_u$) corresponds to the mean square root of the plateau region (upper surface) and *Rvq* ($=\sigma_l$) corresponds to the mean square root of the valley region (lower surface). The knee-point (r_k, z_k) defines the separation of the upper and lower surfaces whilst *Pd* provides the distance between their mean surfaces (z_{mu}, z_{ml}). This probability material ratio curve method has been used by Whitehouse [5], Malburg et al. [6],

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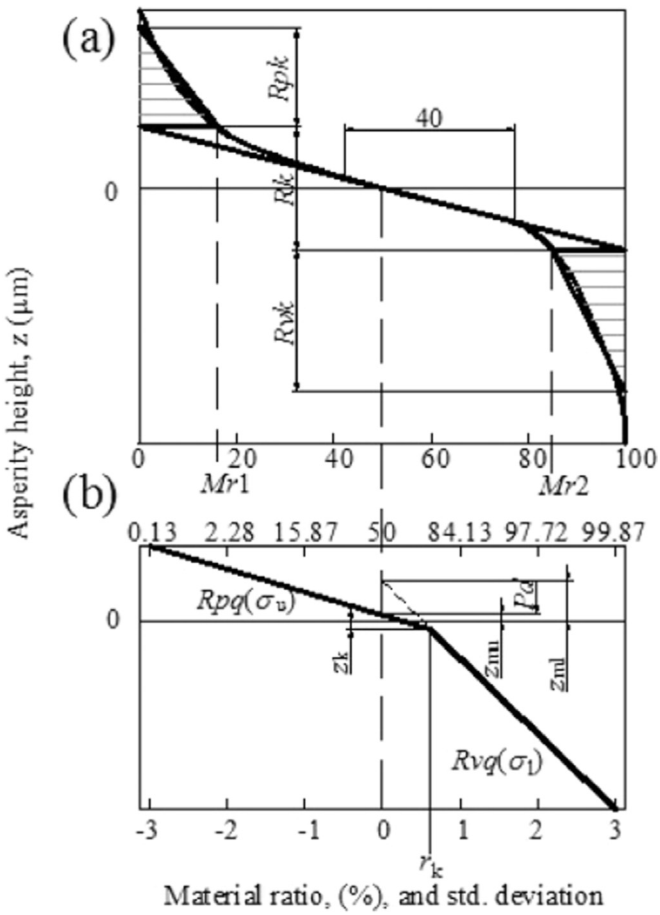

Fig. 1. Characterization of a two-process or worn surface.

Sannareddy et al. [7], Leefe [8] and Pawlus and Grabon [9] to characterize bi-Gaussian surfaces.

However, all the above works [5–9] used the segmented regression technology to differentiate between the component strata contained within the stratified surface. The process consists in 1) defining a certain point of the probability material ratio curve as the knee-point to divide the curve into two regions; 2) linearly fitting each region to obtain the cumulative error which is the sum of the fitting error at each point; 3) repeating first two steps successively from the end of the curve to the other; 4) searching the optimized knee-point with a minimum cumulative error; 5) outputting the intercepts and slopes at the optimized knee-point, i.e., (z_{mu}, σ_u) relating to the upper surface and (z_{ml}, σ_l) relating to the lower surface; 6) dividing z into the upper and lower surfaces based on the selected knee-point, and calculating other surface parameters such as correlation length, summit density and mean summit curvature radius within each component surface. Although the segmented regression is an effective method, it has two drawbacks. The first one is that it arbitrarily assumes the probability material ratio curve consisting of two straight lines with a knee-point. In fact, the probability material ratio curve should have a smooth transition region, which is a result of the gaps induced in the original plateau profile by the deep valleys in the rough profile [7] and the unity-area demand on the PDF. The second one is that the segmented regression prefers to focus on the large-scale roughness (higher slope) because of the principle of minimum cumulative error for searching the optimized knee-point, and therefore easily induces a large fitting error for the surface with the small-scale roughness (lower slope), leading to the message loss of the small roughness-scale surface.

In the aspect of reconstructing rough surface, broadly speaking, three main methods can be used: the autoregressive method [10–12], the moving average method [13–15] and the function series [16–18]. Direct or fast Fourier transform (FFT) can be used in these methods to generate a Gaussian or non-Gaussian surface, where the latter is more efficient and needs a smaller storage space. To generate a non-Gaussian surface, the Johnson translation system [19] with auxiliary algorithms [20,21] is used to impose the prescribed skewness and kurtosis to the initial Gaussian series. Minet et al. [22] have used the Johnson approach [19–21] to reproduce simulated surfaces for three worn surfaces. Even if the simulated non-Gaussian surface generated by the Johnson reconstruction approach could capture the roughness, correlation length, skewness and kurtosis of a worn surface, it still ignores the stratified characteristic. Therefore, the bi-Gaussian reconstruction approach consisting in four steps is a good alternative: 1) generating two Gaussian surfaces with their own autocorrelation function and standard deviation; 2) choosing the distance between the mean surfaces of the two surfaces; 3) generating a new surface by remaining the minimum of the two Gaussian surfaces at each point; 4) updating the new surface relative to its mean value. Pawlus [23] has simulated some bi-Gaussian surfaces with specified component surface parameters.

The aim of the present study is to propose a continuous separating method instead of the segmented regression method. This new separation method arises from the revision of the PDF for the first drawback, and sequentially overcomes the second drawback. Then, the new separation method is carried out on both simulated bi-Gaussian and experimental worn surfaces to evaluate its performance. For the comparison purpose, the segmented regression method is also performed.

2. Continuous separation method

2.1. Surface combination theory

Fig. 2 illustrates the surface combination theory. Assuming a surface S_1 following a height distribution with a PDF f_1, the probability to find a point below a certain height z can be given by the cumulative distribution function (CDF) $P_1(z)$. The relation between these two functions is

$$P_1(z) = \int_{-\infty}^{z} f_1(z)dz. \tag{1}$$

It means that if the surface S_1 is cut by a horizontal plane of height z, $P_1(z)$ is the projected area of the points below the plane. By this, $f_1(z)$dz corresponds to the additional projected area when the plane transfers from z to $z+$dz. Here, the areas are normalized by the total area. The same procedure is also carried out on another surface S_2.

Now, if we tend to generate a new surface S_3 by remaining the minimum of the two above surfaces at each point, i.e., $S_3=\min(S_1, S_2)$, the PDF of S_3 is not simply the sum of f_1 and f_2. In fact, when a truncation plane is done at z and then transferred with an increment dz, an additional projected area is created. Yet, it is not simply obtained by $f_1(z)$d$z+f_2(z)$dz. Indeed, for the surface S_1, it is impossible to create additional projected area from the part where some points of the surface S_2 already exist. Namely, it is possible to create additional projected area from a reduced area $(1-P_2)$. This limitation of creating additional projected area also exists for the surface S_2. Thus, the PDF of S_3 is

$$f_3 = f_1(1-P_2)+f_2(1-P_1). \tag{2}$$