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Feature-preserving filtering for micro-structured surfaces using combined sparse regularizers

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ABSTRACT

Micro-structured components have been widely used in modern opto-electronics systems, but effective characterization methods for structured surfaces are still of lack. Reliable filtering is required to separate the salient structural features and micro-textures, so that the characteristic parameters of the geometrical features can be obtained accurately. Conventional filtering methods cannot preserve sharp features very well. In this paper, a feature-preserving filtering method is proposed using the combined sparse regularizers. In addition to the fidelity term, two regularization terms involving the first order and second order derivatives respectively are taken in the optimization objective function, so that the filtered data can be divided into a piecewise constant part and a piecewise smooth part. Taking the advantage of sparsity of ℓ_p-norm ($0 < p < 1$), the regularized filtering method can achieve good balance between feature preserving and noise removal. An iterative reweighted algorithm is used to solve the complex objective function. Numerical experiments and comparisons are presented to show that the proposed method is capable of preserving features like sharp edges and corners and suitable for a wide variety of surface shapes.

1. Introduction

Micro-structured components contain micro-structured features, typical examples of which are MEMS, micro-lens arrays, gratings, etc. [1,2]. Due to the special opto-electro-mechanical characteristics, micro-structured components have been wildly used in different areas such as photoelectric imaging, optical fiber communication, laser technology, automotive and defense [3]. Because the surface topographies of micro-structured components, especially the qualities of geometric features, directly determine their performance, it is necessary to analyze and characterize the micro-structured features. The existing surface characterization methods are mainly based on the Fourier transform, and topography components are classified according to their Fourier frequencies, such as form, waviness and roughness. Globally defined statistic parameters such as the arithmetic average value and root-mean-square value are employed to measure the surface qualities [4]. However, these parameters do not reflect the local geometric features of micro-structured surfaces and cannot be related to actual manufacturing process conditions. As a result, these methods are not suited for characterizing micro-structured surfaces.

To assess the surface qualities of micro-structured surfaces, local geometric features have to be segmented. Differential methods, such as the Sobel, Roberts and Laplacian operators [5–7], are commonly used. Yet considering the tool marks, vibration and material defects generated in the process of manufacture, the actual surfaces contain irregular micro textures, which are sensitive to the differential operators and prone to the failure of segmentation. To handle this problem, the data should be filtered before segmentation, as shown in Fig. 1. However, most of the filtering methods behave well for static stochastic surfaces only. Once applied to micro-structured surfaces, the halo effect and distortion will occur at the sharp corners. As a consequence, the capability of feature-preserving is required for the filtering methods applied to micro-structured surfaces.

In this paper, a new feature-preserving filtering method is proposed. By using an optimization function with combined sparse regularizers, the underlying structures are assumed to be composed of a piecewise constant part and a piecewise smooth part. The rest of the paper is organized as follows. In Section 2, some related filtering methods are reviewed. Section 3 introduces the

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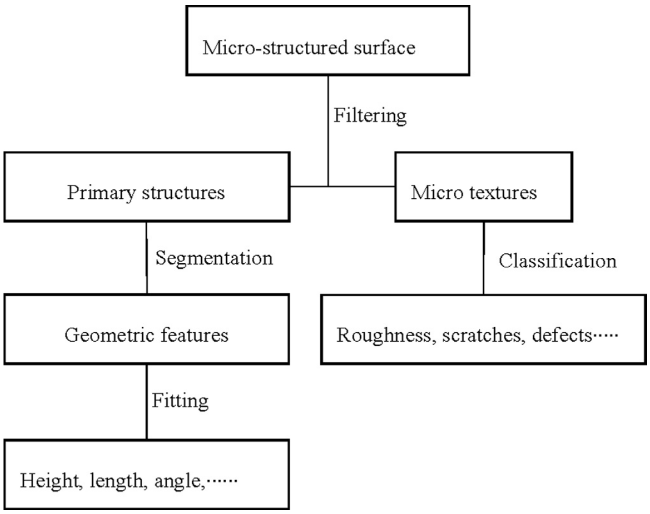

Fig. 1. The characterization of micro-structured surface.

proposed method in detail. Experiments and discussion are presented in Section 4. Finally, the paper is summarized in Section 5.

2. Related work

The most widely used filtering method is the Gaussian filter [8], which uses a Gaussian kernel for mathematical convolution. Using the Gaussian weighted average of the pixels in a fixed window, the underlying smooth profile can be estimated. This method is simple to implement, but sharp features will be blurred. Bilateral filter [9] makes an improvement by adding a weight in the Gaussian kernel to measure the height difference between data points. The filtered results are less influenced by the neighbourhood points compared to the Gaussian filter, therefore bilateral filter has better capability of feature preserving. The nonlocal means filter [10] uses a similar weight on measured heights. Differently, the weight is measured patch-wisely. The drawback of this method is its high computational complexity. Xiong and Ding [11] gave a universal denoising paradigm for the weighted average filtering methods from the perspective of signal's attribute analysis. Though this method can be extended to include any attribute, it is still a laboursome task to identify and quantify the features of interest.

Another class of filtering methods are the energy optimization-based methods. Usually there are two terms in the function: the fidelity term and the regularization term. The former puts similarity constraints on the estimated data and the latter gives a sparse regularization to preserve important features. The Rudin-Osher-Fatemi (ROF) model [12], also called the total variation (TV) method, is one of the most classic methods. To remove the noise, it forces the data gradient to be sparse using the ℓ_1-norm regularization term. Based on this model, a variety of methods with different fidelities or regularizers are proposed. Chan and Esedoglu [13] used a ℓ_1-norm fidelity term for image denoising, and interesting new applications like multiscale image decomposition are suggested. A sparser ℓ_0-norm regularization term is studied in [14,15] for image smoothing. Although these TV-based models can preserve sharp edges, some limitations still restrict their performance. For example, smooth transition regions are always rough due to the stair effect. To overcome this drawback, a regularization term containing high-ordered derivatives is adopted. Chan et al. [16] added a nonlinear second order term to the TV functional. The acquired performance is better except for its slow convergence rate. Lysaker et al. [17] created the Lysaker-Lundervold-Tai model, which replaces the first ordered derivatives with second ordered derivatives in the regularization term. Although this makes the function more difficult to solve, it preserves smooth regions much better than ROF. Other methods using the ℓ_2 norm regularization can also have a smoothing effect, but edges may be blurred. Chen et al. [18] proposed an adaptive denoising method. Using the curvature as a criterion to identify sharp edges, the regularization is approximated with either a TV norm or a ℓ_2 norm when necessary. But the criterion may lose effectiveness when the noise is large.

Considering that most of the existing methods work well only within a limited range, and cannot be applied to complex structures. Some specially designed methods are effective, but they are complicated and time-consuming. The method proposed here exerts the idea of decomposing signals into subcomponents on data filtering [19–21]. By simply optimizing an objective function with combined sparse regularizers, important features can be preserved well with noise removed successfully.

3. Optimization method with combined sparse regularizers

3.1. The optimization function

Assume that the underlying data for a micro-structured surface can be divided into two parts, a piecewise constant (PC) component and a piecewise smooth (PS) component. Here an optimization objective function is defined as follows:

$$\min_{u_{01},u_{02}} \|u_1 - u_{01} - u_{02}\|_2^2 + \gamma\|\nabla u_{01}\|_{p_1}^{p_1} + \mu\|\nabla^2 u_{02}\|_{p_2}^{p_2} \tag{1}$$

where u_1 is the measured data. u_{01} and u_{02} are the PC and PS components, respectively. γ and μ are non-negative parameters to balance the three terms. p_1 and p_2 are real norms between 0 and 1. ∇ and ∇^2 are the first-order and second-order differentiation operators. ∇u_{01} is defined as

$$(\nabla u_{01})_{i,j} = (D_x^+ u_{01}, D_y^+ u_{01})^T$$

and $\nabla^2 u_{02}$ is defined as

$$(\nabla^2 u_{02})_{i,j} = \left(D_x^-(D_x^+ u_{02})_{i,j}, D_x^+(D_y^+ u_{02})_{i,j}, D_y^-(D_x^- u_{02})_{i,j}, D_y^-(D_y^+ u_{02})_{i,j}\right)^T$$

Symbols such as D_x^+, D_x^-, D_y^+ and D_y^- are differentiation operators and we refer the readers to [22,23] for more details.

The objective function consists of three terms. The first term is the fidelity term to ensure the estimated data not far away from measured one. The second and third terms are regularizers to control the smoothness of the filtered surface. To reconstruct a PC component, $\|\nabla u_{01}\|_{p_1}^{p_1}$ is adopted. A smaller $\|\nabla u_{01}\|_{p_1}^{p_1}$ forces the gradient of u_{01} to be sparse, an ideal situation of which is that most of the gradients of u_{01} are zero and non-zero gradients only remain at actual steps. This is exactly the definition of PC. Similarly, a smaller regularizer $\|\nabla^2 u_{02}\|_{p_2}^{p_2}$ forces the change in gradient, namely curvature, of u_{02} to be sparse, where most of the curvatures of u_{02} are zero and non-zero curvatures only remain at actual edges. This term can give a better approximation for the PS component. The combination of u_{01} and u_{02} is constrained by the first term to reconstruct the underlying micro-structured surface. Once the minimum of the objective function is achieved, detailed textures can be removed and features are preserved. Here the ℓ_p-norm with $0 < p < 1$ is used in the two regularizers, considering its excellent sparsity [24]. It is very suitable for feature-preserving filtering, where the main features are always sparse. But it is also a non-convex problem and difficult to be solved. We use the iterative reweighted algorithm to solve this problem.