Measurement 79 (2016) 137–146

Contents lists available at ScienceDirect

Measurement

journal homepage: www.elsevier.com/locate/measurement

Segmentation of non-stochastic surfaces based on non-subsampled contourlet transform and mathematical morphologies

Linfu Li [a,b], Xiangchao Zhang [a,*], Hong Xiao [c], Min Xu [a]

[a] Shanghai Engineering Research Center of Ultra-Precision Optical Manufacturing, Fudan University, Shanghai 200438, PR China
[b] School of Information Engineering, Guizhou Minzu University, Guiyang 550025, PR China
[c] Laboratory of Precision Manufacturing Technology, China Academy of Engineering Physics, Mianyang 621900, PR China

ARTICLE INFO

Article history:
Received 9 December 2014
Received in revised form 30 July 2015
Accepted 10 August 2015
Available online 12 November 2015

Keywords:
Non-stochastic surface
Segmentation
Contourlet
Morphology
Multi-scale geometry analysis

ABSTRACT

In precision engineering, non-stochastic surfaces are employed more and more widely in advanced functional components. The statistically defined amplitude or spatial parameters commonly adopted for stochastic surfaces are not suited to characterize non-stochastic surfaces. It is required to segment the whole surfaces into regions and assess the qualities of the geometrical features individually. The non-subsampled contourlet transform (NSCT), composed of bases oriented along various directions in multiple scales, is a shift-invariant representation with good directional/scale localization. In this paper, by combining NSCT and mathematical morphologies, a novel surface segmentation method is proposed. The multi-scale properties of NSCT make this method flexible in extracting salient borderlines between feature regions, and the mathematical morphological operators are employed subsequently to deal with occasional broken filaments or over-segmentation. Experimental results are presented to demonstrate the superiority of the proposed method on the identification and segmentation of various morphological features with complex boundaries.

1. Introduction

With the rapid development of advanced design and precision manufacturing technologies, micro-structured surfaces with deterministic patterns or complex morphological features are more and more extensively used in the fields of mechanical engineering, electronics, optics and biology, such as microcircuit, micro-optical elements, and MEMS devices [1]. As a consequence, accurate measurement and reliable characterization of the topographies of structured surfaces have become urgent tasks in surface metrology.

The conventional surface characterization methods are established on the foundation of the Fourier transform, which decomposes a surface into a combination of different Fourier frequencies. The surface quality is assessed by some amplitude or spatial parameters statistically defined on the whole surface. However a lot of engineering surfaces are non-stochastic. The non-stochastic surfaces comprise a dominant topology pattern, with structured features designed to meet a specific function [2,3]. The attribute information, especially the geometrical characteristic parameters like heights, angles, and radii of individual features, is more relevant to the functionalities in practical applications than the statistical texture parameters. As a result the geometrical structures need to be segmented [4]. The edges between adjacent regions are important salient features of structured surfaces. Only with correct edge detection different structured elements can be identified properly, so as to determine their characteristics accurately.

---

[*] Corresponding author. Tel.: +86 21 51630347.
E-mail address: zxchao@fudan.edu.cn (X. Zhang).

http://dx.doi.org/10.1016/j.measurement.2015.08.014
0263-2241/

2. Review of related work

Traditional edge detection methods are based on differential operators in the spatial domain. Such operators include Prewitt, Roberts, Sobel, Laplacian, Log, Canny and so on [5]. These methods determine the candidate edge points based on the first or second order derivatives, and then extract the edges by appropriate thresholding. These operators can detect steps accurately, but the borderlines between continuous slopes cannot be identified. Therefore these methods are unsuited for the segmentation of complex non-stochastic surfaces.

Recently there has been tremendous development of computational tools for surface segmentation. An edge detector using the zero crossing of the Laplacian of Gaussian (LoG) was proposed by Marr and Hildreth [6]. Lindeberg developed an edge detecting method using the derivatives of the Gaussian function over scale-space [7]. A watershed segmentation method based on the Wolf pruning was developed by Scott. It is the only surface segmentation method defined in the ISO TC/213 standards [8]. But this method divides feature regions based on the height information only; as a result it cannot effectively deal with those features with different slopes, e.g. the facelets of pyramidal or sawtooth structures. Senin et al. proposed to segment surfaces by clustering based on the homogeneity of local surface features [9]. Tsuchie et al. introduced a new vertex clustering method using the Student-*t* distribution model to segment industrial design objects [10]. Holz and Behnke segmented planes and other geometrical primitives using a robust reconstruction approach with approximate polygonal meshes [11].

With the development of the multiscale geometric analysis, many effective edge detection methods have emerged. A simplified version of the Gabor wavelets was used for edge detection by Jiang [12]. The 2D discrete rotationally invariant wavelets were combined with the 2D directional wavelets in edge detection by the non-maximum suppression [13]. Although the wavelet transform has advantages in low entropy and multi-resolution, but it cannot effectively deal with line or curve singularities. The poor directional representativity severely limits its applications. As a consequence some directional multiscale transformations are adopted for segmentation. Li et al. proposed to detect straight edges based on the ridgelet transform [14]. An edge detection method combining the curvelet transform and other operators was introduced by Zhou et al. [15] for processing synthetic aperture radar images and tire laser shearography images. But these representations are not sufficiently sparse for the boundaries between complex surface features, thus they will lead to false segmentation results in practice.

3. A new segmentation method for non-stochastic surfaces

Among the directional multiscale representations, the non-subsampled contourlet transform (NSCT) developed by Cunha et al. is one of the most popular one [16]. It not only keeps the advantages of wavelets but also has remarkable superiorities on multi-directionality, real anisotropy and full shift-invariance.

3.1. Non-subsampled contourlet transform

NSCT is a fully shift-invariant version of the original contourlet transform. This property is desirable in edge detection of structured surfaces. NSCT is based on the non-subsampled pyramids filter banks (NSPFB) and the non-subsampled directional filter banks (NSDFB). During decomposition any downsampling in the transform domain is avoided, thus there will be no frequency aliasing in the lowpass subband. Furthermore the multiscale and directional decomposition stages are independent of each other. The numbers of decomposition directions are flexible and can be set any value of 2^{l_j}. Here l_j is a parameter defined at scale j, $1 \leqslant j \leqslant J$, with J the number of decomposition scales. Then one surface of large scale and $\Sigma\, 2^{l_j}$ subband surfaces of small scales can be obtained. Unlike the standard contourlet transform, all of the decomposed subbands of NSCT have the same resolutions with the raw surface. That is to say, the NSCT coefficients of each subband are of one-to-one correspondence with the original surface in the spatial domain. Needing no inverse transformation, the edges can be obtained by fusing the multi-scale data. A brief implementation diagram of NSCT is shown in Fig. 1. To show its capabilities of multiscale and directional representation, some basis functions of NSCT in the spatial domain are presented in Fig. 2. Further details can be found in literature [16].

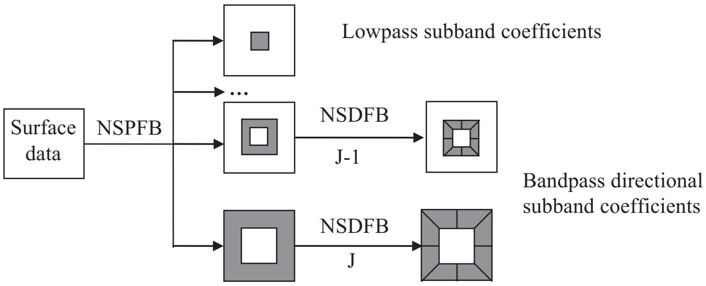

Fig. 1. The decomposition scheme of NSCT.