STABCC: A New 3-D Surface Topography Algorithm Based on Contourlet Transform and Correlation Theory

Jun Wang*[a,b], Yan Kang[c], Lijun Xu[a]

[a]School of Mechanical Science & Engineering, Huazhong University of Science and Technology; [b]College of Mechatronics Engineering，china jiliang university; [c]The youse mapping &conveying institute of zhe jiang

ABSTRACT

In machining and testing fields, 3-D surface topography evaluation is always one of the hottest study issues. Especially, in advanced integrate circuit and nanometer manufacture techniques where surface spraying and thin film plating are commonly applied for, anisotropy behavior in surface topography is rather obvious and existent 3-D surface topography evaluation is not enough in expressive force.

Based on the discussing about that the advantages and disadvantages of all existent filtering methods. The contourlet Transform (CT) which may provide tight bracing and mutliscale analysis was introduced. And a new 3-D surface topography evaluation filtering algorithm is presented. This algorithm has some excellent performances such as multiscale analysis, time-frequency-localization and multidirections. Especially, the algorithm is good at describing high dimensions data. Meanwhile, on the assumption that noise comply with Gaussian distributing, according to the theory that noise is not correlated with signal, STABCC that depress noise was designed.

The surface topography of a part was measured with WIVES. The data of measurement was processed by STABCC. Experiment result indicates that STABCC can reliably obtain benchmark of evaluation. And the surface information of measured part can be extracted and analyzed without distortion. Comparing with existent 3-D surface topography evaluation methods, STABCC is preponderant in practicality of engineering surface evaluation.

Keywords: Contourlet Transform, Surface topography, Filtering, Correlation

1. INTRODUCTION

The surface topology is an important factor affecting part performances (such as friction, abrasion, lubrication, corrosion, failure, coating and painting etc.). In machining part, different feature would come into being according to relevant machining techniques (for example turning, milling and grinding). The variation of machining condition will influence the variation of surface topology. Thus, if the topology of machined surface is decomposed to different space and frequency bands and these decompositions can be corresponded with the variation of a certain machining process. A testing technique will be developed to monitor machining process by analyzing variation of surface topology. The preconditions of building this relationship are: to extract different surface features correctly; to create an effective analysis method for these features, i.e., to establish the relation between the variation of the surface features and the variation of machining conditions [1].

Accurately extracting surface features are greatly useful for evaluating surface function and enhancing part performance. They include extracting not only roughness, waviness and form of separated surface but also multiscale topology features (the peaks/pits and ridges/valleys) without aliasing along the edges of these features [2]. Further more, along with the developing of science and technology, the demand for surface quality has been enhanced to nanometre scale, even to atom scale. Surface measurement technology has been developed to 2-D surface from 1-D profile. The surface of nanometer scale contains more abundant and finer information than traditional one. Accordingly, more advanced surface analysis technologies and methods are demanded to accurately extract useful information from these measured surfaces.

The traditional surface feature extraction focuses on surface roughness analysis where midline evaluation benchmark and filtering are used for long time. The midline evaluation benchmarks mainly include Least Square Regression midline and Arithmetic Average midline as well as Polynomial fit midline. The filters include 2RC filter, spline filter, Gaussian filter, Gaussian regression filter and Gaussian robust filter derived from Guassian filter [3]. The evaluation of surface function features requires 3-D analysis and evaluation. The multiscale analysis technique was introduced along with the

3rd International Symp. on Advanced Optical Manufac. and Testing Tech.: Advanced Optical Manufacturing Technologies, edited by Li Yang, Yaolong Chen, Ernst-Bernhard Kley, Rongbin Li, Proc. of SPIE Vol. 6722, 67223I, (2007) · 0277-786X/07/$18 · doi: 10.1117/12.783544

development of space surface feature evaluation. Meanwhile, MOTIF based on surface morphology has made a great progress too. It has been extensively applied at surface evaluation of car's armor plate and makes success in evaluation of MEMS parts.

By dynamical changing the size of frequency window in analysis, the wavelet analysis provides space and time locating capability which can not been provided from base function derived from sine signal or pulse function. Nevertheless, in 2-D and 3-D data processing, wavelet analysis meets difficulty too. The cause is that wavelet is decomposed just in horizontal and vertical direction. And in higher dimension information, direction of the useful data is complicated. Thus, the efficiency and veracity of wavelet analysis is damaged. In order to solving this problem, many new methods are put forward.

In recent years, the evaluation method of surface analysis has been greatly developed. The ameliorated space surface evaluation method provided possibility for dynamical monitoring surface machining process and further function evaluation. In this paper, on the basis of recent development of signal processing technology, we further explore multi-scale analysis method of surface topology based on CT. The CT and correlation theories are introduced into the areas of surface analysis in this study. As a result, the inherent shortcoming of traditional analysis method is solved and exactly extraction on surface features is realized.

2. CONTOURLET TRANSFORM

2.1 Comparison with wavelet transform

Wavelet transform (WT) would take many wavelet coefficients to accurately represent even one simple 2-D curve, so CT were developed as an improvement over WT in terms of this inefficiency. The CT has the multiscale and time-frequency-localization properties of WT; meanwhile it offers a high degree of directionality and anisotropy. Precisely, CT involves basis functions that are oriented at any power of two's number of directions with flexible aspect ratios. With such richness in the choice of basis functions, CT can represent any 1-D smooth edges with close to optimal efficiency. Fig.1 shows that compared with WT, CT can represent a smooth contour with much fewer coefficients [4].

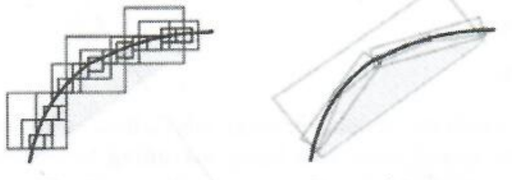


Fig.1. Wavelet versus Contourlet: illustrating the successive refinement by the two systems, where Contourlet using fewer coefficients than wavelet.

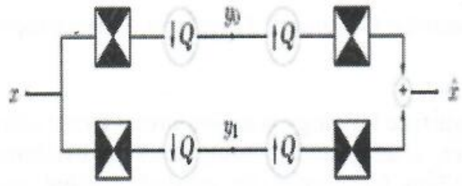


Fig.2. 2-D frequency partition using quincunx filter banks with fan filters. The black regions represent the ideal frequency supports of each filter. Q is a quincunx sampling matrix.

2.2 Pyramidal directional filter bank and Iterated directional filter banks

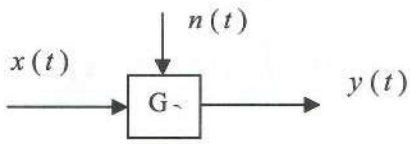
Contourlets are implemented by the pyramidal directional filter bank (PDFB) that is a cascade of a Laplacian pyramid (LP) and a directional filter bank (DFB) [5]. Due to this cascade structure, multiscale and directional decomposition stages in the CT are independent of each other. We can decompose each scale into any arbitrary power of two' s number of directions, and different scales can be decomposed into different numbers of directions.

Bamberger and Smith [6] constructed a 2-D directional filter bank (DFB) that can be maximally decimated while achieving perfect reconstruction. To obtain the desired frequency partition, a complicated tree expanding rule has to be followed for finer directional subbands [7]. In [8], a new construction was proposed for the DFB that avoids modulating the input image and has a simpler rule for expanding the decomposition tree. This DFB is intuitively constructed from two building blocks. The first building block is a two-channel quincunx filter bank [9] with fan filters (see Fig.2) that divides a 2-D spectrum into two directions: horizontal and vertical. The second building block of the DFB is a shearing operator, which amounts to just reordering of image samples.

3. FOUNDING RULE FOR DENOISING AND FILTERING

Essentially, CT filters noise from signal by means of limited iterative decompositions and reconstructions. But the levels of decomposition and the threshold value of reconstruction is very dependent on individual experience. Therefore, there is strongly subjectivity when the data is processed. According to relational theories of that signal is not correlated with noise, an objective filtering rule is proposed in this paper.

In a general way, the signals containing noise are processed as Fig.3.



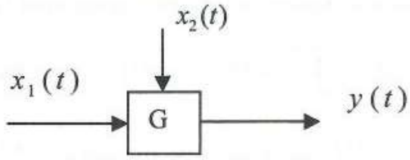


Fig.3. Signals flow chart. Where $x(t)$ is input signals, $n(t)$ is noise, G represents processing system and $y(t)$ is output signals.

Fig.4. Signals flow chart. Where $x_1(t)$ is waviness signals, $x_2(t)$ is roughness signals, G represents processing system and $y(t)$ is output signals.

Thus, the cross correlation function of input signals and output signals is:

$$r_{xy}(t) = \int_{-\infty}^{+\infty} [x(t) + n(t)] * y(t-\tau) dt \tag{1}$$

Unwrapping expression (1), the cross correlation function may be written as following:

$$r_{xy}(t) = \int_{-\infty}^{+\infty} x(t) * y(t-\tau) dt + \int_{-\infty}^{+\infty} n(t) * y(t-\tau) dt \tag{2}$$

The autocorrelation function of output signals is:

$$r_{y^2}(t) = \int_{-\infty}^{+\infty} y(t) * y(t-\tau) dt \tag{3}$$

In the ideal case that noise may be fully filtered out and the direct current part of both signal and noise are also taken out, the first part of the expression (2) is an autocorrelation function of output signals, and the second part is zero. The difference between expression (1) and expression (2) is described with e (t), thus,

$$e(t) = r_{xy}(t) - r_{y^2}(t) = \int_{-\infty}^{+\infty} x(t) * y(t-\tau) dt + \int_{-\infty}^{+\infty} n(t) * y(t-\tau) dt - \int_{-\infty}^{+\infty} y(t) * y(t-\tau) dt = 0 \tag{4}$$

Based on these, the levels of decomposition and reconstruction may be controlled; consequently, noise may be filtered from signal according to our demand.

Furthermore, the information contained in surface topography may be classified into figure information, waviness information and surface roughness information. We supposed that noise has been filtered, the information may be fractionized as:

$$x(t) = x_1(t) + x_2(t) \tag{5}$$

There $x_1(t)$ represents waviness information and $x_2(t)$ represents roughness information. The new information flow may be described as fig.4.

Similarly, we still describe cross correlation function of input signals and output signals with $R_{xy}(t)$; and described autocorrelation function of output signals with $R_{y^2}(t)$. Consequently,

$$R_{xy}(t)=\int_{-\infty}^{+\infty}[x_1(t)+x_2(t)]*y(t-\tau)dt \tag{6}$$

$$R_{y^2}(t)=\int_{-\infty}^{+\infty}y(t)*y(t-\tau)dt \tag{7}$$

$E(t)$ is used to describe the difference between expression (6) and expression(7). We get:

$$E(t)=R_{xy}(t)-R_{y^2}(t)=\int_{-\infty}^{+\infty}[x_1(t)+x_2(t)]*y(t-\tau)dt-\int_{-\infty}^{+\infty}y(t)*y(t-\tau)dt \tag{8}$$

Under ideal case, the roughness information $x_2(t)$ has been fully filtered out. $y(t) = x_1(t)$.

Thus, an expression may be obtained by cleaning up the expression (8).

$$E(t)=R_{xy}(t)-R_{y^2}(t)=\int_{-\infty}^{+\infty}x_2(t)*y(t-\tau)dt \tag{9}$$

It can be estimated by relative definition about waviness and roughness. Hereby, the waviness information and roughness information may be distinguished.

4. EXPERIMENT AND ANALYSIS

Two experiments have been done in this study. In experiment 1, we compared CT with WT in their filtering performance. The result shows that the CT takes advantages to the WT in 2-D information processing. In experiment 2, the STABCC filter structured by contourlet filters and correlation functions was used to processing 3-D surface profile information. And the result showed that CT is better than WT, but it didn't represent good enough in the edges.

4.1 Comparison of wavelet with contourlet

On the basis of contourlet box provided by Minh. N.DO, we rewrote some codes and processed a 512*512 gray-scale image 'Lena'. The result was shown as following:

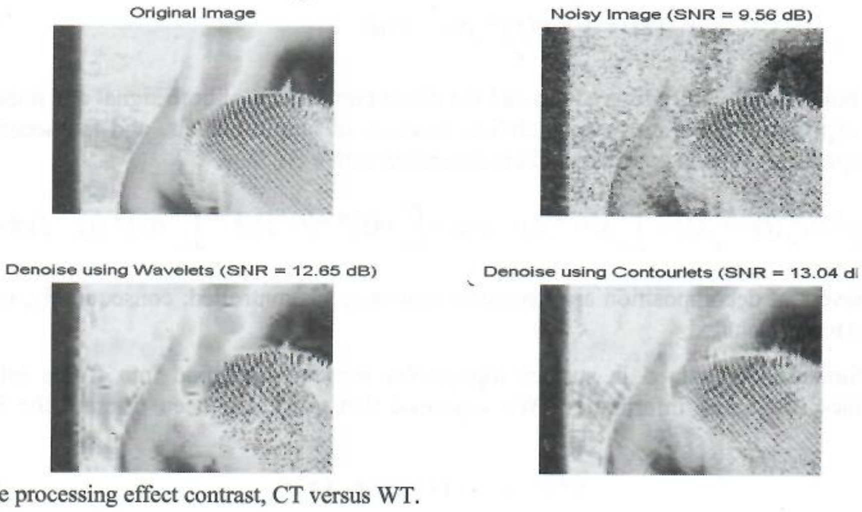


Fig.5. 2-D image processing effect contrast, CT versus WT.

Both from subjective and objective aspects, we all thought CT is better than WT.

4.2 Test of 3-D surface topology

We measured a sample with wives made by HUST (Huazhong University of Science &Technology). And the tested data was processed with STABCC. The testing result is illustrated as following:

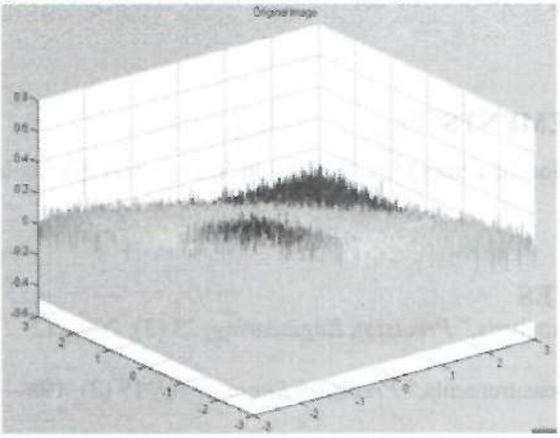


Fig.6. Original 3-D image containing noise, roughness, waviness and form information.

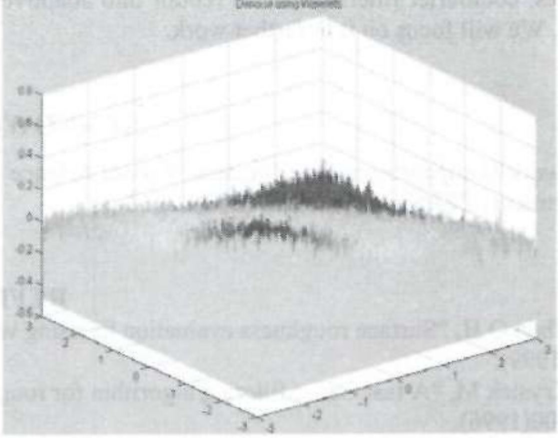


Fig.7. 3-D image processed with WT.

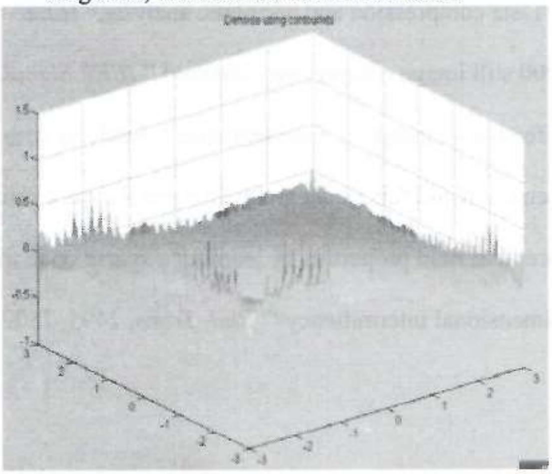


Fig.8. 3-D image processed with CT.

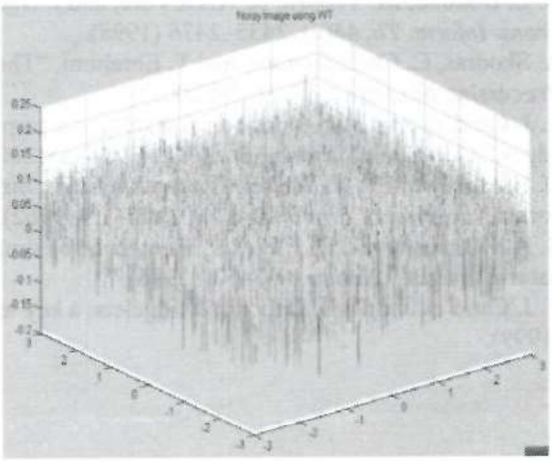


Fig.9. Noise image processed with WT.

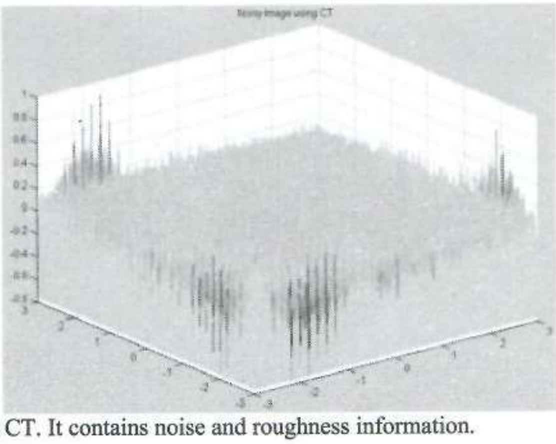


Fig.10 3-D image processed with CT. It contains noise and roughness information.

5. CONCLUSION AND FURTHER WORK

Experiment result shows that contourlet filtering is better than 2-D wavelet filtering in processing 2-D data. And the effect is expected well on condition that the algorithm is optimized. According to experiment 2, a conclusion can be draw that contourlet filtering represents outstanding performance in 3-D data processing. Combined with correlation theories, contourlet filtering can be rebuilt into adaptive filtering STABCC. Its shortcoming is distortion produced on edges. We will focus on it in further work.

ACKNOWLEDGEMENTS

This work is supported by the National Natural Science Foundation of China (50175037) and Science and Technology Department of Zhejiang Province (2006c21127)

REFERENCES

1. Chen Q H, "Surface roughness evaluation by using wavelets analysis," *Precision Engineering*, 23 (3), 209-212 (1999).
2. Krystek M, "A fast Gauss filtering algorithm for roughness measurements," *Precision Engineering*, 19 (2), 198 – 200(1996).
3. W. Zeng, X. Jiang, P. Scott, "Metrological Characteristics of Dual Tree Complex Wavelet Transform for Surface Analysis," *Measurement Science and Technology,* 29 (7), 125 – 131(2002).
4. D. L. Donoho, M. Vetterli, R. A. DeVore, and I. Daubechies, "Data compression and harmonic analysis," *IEEE Trans. Inform. Th*, 44(6), 2435–2476 (1998).
5. A. Skodras, C. Christopoulos, and T. Ebrahimi, "The JPEG 2000 still image compression standard," *IEEE Signal Processing Magazine*, 18, 36–58(2001).
6. E. J. Cand`es and D. L. Donoho, "Curvelets – a surprisingly effective nonadaptive representation for objects with edges," *Curve and Surface Fitting*, 28(5), 36–58(2001).
7. D. H. Hubel and T. N. Wiesel, "Receptive fields, binocular interaction and functional architecture in the cat's visual cortex," *Journal of Physiology*, 160, 106–154(1962).
8. B. A. Olshausen and D. J. Field, "Emergence of simple-cell receptive field properties by learning a sparse code for natural images," *Nature*, 607–609(1996).
9. E. J. Cand`es and D. L. Donoho, "Ridgelets: a key to higher-dimensional intermittency?" *Phil. Trans*, 2495–2509 (1999).