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A fast and adaptive bi-dimensional empirical mode decomposition approach for filtering of workpiece surfaces using high definition metrology

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ABSTRACT

The surface topography of workpieces has an important influence on the final performances of the product. The digital filtering is a critical step to analyze the surface topography of workpieces. Bi-dimensional empirical mode decomposition (BEMD) approach is superior to conventional filtering approaches in the analysis of non-stationary and non-linear data. High definition metrology (HDM) can generate massive point cloud data to represent the three-dimensional (3D) surface topography of workpieces, which provides a new opportunity for surface topography analysis. This paper develops a fast and adaptive bi-dimensional empirical mode decomposition (FABEMD) approach for filtering of workpiece surfaces using HDM. Firstly, the neighboring window algorithm is presented to extract local extrema and draw the extrema spectrum. Secondly, the adaptive window algorithm is developed to automatically select the optimal window size of the order statistics filter, and plot the envelope spectrum. Finally, the average smoothing filter is presented for smooth filtering and generating of the mean envelope. The performance of the proposed FABEMD-based filter is validated by a simulated surface data and three real-world surface data. Compared with Gaussian filter (ISO 11562:1996, ASME B46.1-2002), the BEMD-based filter and the recent shearlet-based filter in the qualitative and quantitative analysis, the proposed FABEMD-based filter is superior for the separation and extraction of different surface components.

1. Introduction

The surface texture is an important index to evaluate the quality of workpieces [1,2], and is generally described from the small to the large scale: roughness, waviness and form. It is well-known that different components of the surface texture have different influences on the functional performance of workpieces. To be specific, roughness is a good indicator of the surface irregularities, thus can be applied to detect errors in the material removal process, and also it has great influence on the workpiece functionality such as wear and friction. Waviness, which may occur from machine or work deflections, chatter, residual stress, vibrations, or heat treatment, has influence on tightness of workpieces. Form may directly affect the assembling performance of workpieces. Therefore, the motivation for separating these components derives from the fact that they have different origins and influences on workpieces functionalities in different ways. It is very important to separate the surface texture into different components before surface topography analysis.

Digital filtering is an essential step to realize the separation process. Filtering of workpiece surfaces has been a hot research topic on account of its importance for surface texture analysis. The traditional filtering approaches such as 2RC filter and Gaussian filter have been firstly studied, and the Gaussian filter is one of the most widely-used standard filtering approaches. However, it is well recognized that it is not robust against outliers. To overcome the shortcoming, some modified approaches such as robust regression Gaussian filter [3], spline filter [4], robust spline filter [5], and morphological filter [6] have been developed. Recent advances in filtering approaches are reviewed in [7,8].

Several researchers develop wavelet-based filtering approaches and apply them to analyze workpiece surfaces. Different from the previous filtering approaches, wavelet-based filters can provide multi-scale analysis since they can divide a surface profile into different frequency components and investigate each component with a resolution matched to its scale. Fu et al. [9]

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adopted the wavelet transform to surface topography analysis and compared different wavelet bases. Orthogonal wavelet bases and biorthogonal wavelet bases were recommended due to their transmission characteristics of the corresponding filters. Jiang et al. [10] proposed a lifting wavelet representation for characterization of surface topography. Josso et al. [11] proposed a frequency normalized wavelet transform for surface roughness analysis and characterization. Wang et al. [12] proposed a modified anisotropic diffusion filter to separate workpiece surfaces into various scale-limited surfaces. Most recently, Du, Liu and Huang [13] presented a shearlet-based filtering approach. The workpiece surface was decomposed into different sub-bands of coefficients with non-subsampled shearlet transform (NSST). Then the surface components at different level were reconstructed based on inverse NSST.

Recently, Huang et al. [14] and Du et al. [15] introduced and improved the empirical mode decomposition (EMD) approach to analyze one-dimensional non-stationary and non-linear signals based on instantaneous frequency. Flandrin [16] proposed the concept of filter banks based on EMD and the corresponding order intrinsic mode functions (IMFs) were combined to achieve the high-pass, low-pass and band-pass filters. Wu and Huang [17] confirmed that the EMD approach had similar filtering characteristics with the wavelet-based approaches. Boudraa and Cexus [18] used different thresholds for each IMF to reconstruct the new filter and realize the signal denoising. Nevertheless, EMD cannot be used to analyze 3D data.

Nunes [19] proposed a bi-dimensional EMD (BEMD) appraoch, which is a two-dimensional (2D) extension of the EMD approach, mainly used for image processing [20], image denoising [21], image edge pattern processing [22] and medical image registration [23], not used for filtering of workpiece surfaces. Moreover, since the window size of order statistic filters in the BEMD approach is not determined adaptively, it frequently does not have the best filtering results. Bhuiyan [24,25] proposed a fast and adaptive BEMD (FABEMD) approach. Simulation results demonstrate that FABEMD is not only faster and adaptive, but also outperforms the original BEMD in terms of the quality of the BIMFs.

With the development of on-line high definition measurement (HDM) technologies, great opportunities are provided for on-line controlling surface quality. A representative of on-line HDM for surface variation measurement is Shapix based on laser holographic interferometry metrology [26], which measures 3D surface height map and gains millions of data points within seconds, and has 150 μm resolution in x–y direction and 1 μm accuracy in z direction. Based on HDM, some researches about surface quality control and engineering applications have been successfully conducted, such as surface classification [27,28], tool wear monitoring [29], form error evaluation and estimation [30,31], volume variation control [32], and flat surface variation control [33]. However, to the best knowledge of the authors, there is no BEMD-based filtering approach for workpiece surfaces using HDM. The high density point cloud data of HDM is large. About one million measurement points are collected from a cylinder head by HDM system. So, HDM needs a fast and adaptive analysis. Therefore, this paper presents a novel fast and adaptive bi-dimensional empirical mode decomposition (FABEMD) approach for filtering of workpiece surfaces using HDM.

The remainder of this paper is organized as follows: The BEMD approach is briefly introduced in Section 2. In Section 3, the proposed approach of filtering workpiece surfaces is presented. In Section 4, a simulation experiment is conducted to validate the feasibility of the presented approach. In Section 5, three case studies using different kinds of workpiece surfaces are presented to show the effectiveness of the proposed approach. In Section 6, the conclusions of this study are drawn.

2. Brief introduction to BEMD

The BEMD approach decomposes a signal into its bi-dimensional IMFs (BIMFs) and a residue based on the local spatial scales. Let the original signal be denoted as $I(x, y)$, a BIMF as $F(x, y)$, and the residue as $R(x, y)$. The original bi-dimensional signal $I(x, y)$ can be decomposed by BEMD

$$I(x, y) = \sum F_i(x, y) + R(x, y) \tag{1}$$

where $F_i(x, y)$ is the i-th BIMF obtained from its source signal $S_i(x, y)$, and $S_i(x, y) = S_{i-1}(x, y) - R_{i-1}(x, y)$.

It requires one iteration or more to obtain $F_i(x, y)$, and the intermediate state of a BIMF in j-th iteration can be denoted as $F_{Tj}(x, y)$. The decomposition steps of the BEMD approach are summarized as follow:

Step 1: Set $i = 1$ and $S_i(x, y) = I(x, y)$.

Step 2: Set $j = 1$ and $ST_j(x, y) = S_i(x, y)$. ST_j represents the input signal of the jth decomposition.

Step 3: Obtain the local maxima map of $F_{Tj}(x, y)$, denoted as $P_j(x, y)$.

Step 4: Interpolate the maxima points in $P_i(x, y)$ and generate the upper envelope, denoted as $U_{Ej}(x, y)$.

Step 5: Obtain the local minima map of $F_{Tj}(x, y)$, denoted as $Q_j(x, y)$.

Step 6: Interpolate the minima points in $Q_i(x, y)$and generate the lower envelope, denoted as $L_{Ej}(x, y)$.

Step 7: Calculate the mean envelope $M_{Ej}(x, y) = (U_{Ej}(x, y) + L_{Ej}(x, y))/2$.

Step 8: Calculate the details of the signal in the decomposition process,$F_{Tj+1}(x, y) = F_{Tj}(x, y) - M_{Ej}(x, y)$.

Step 9: Check whether $F_{Tj+1}(x, y)$ follows the BIMF properties by finding the standard deviation (SD), denoted as D (Eq. (2)), between $F_{Tj+1}(x, y)$and $F_{Tj}(x, y)$, and compare it with the desired threshold.

$$D = \sum_{x=1}^{M} \sum_{j=1}^{N} \frac{|F_{T\,j+1}(x, y) - F_{T\,j}(x, y)|^2}{|F_{T\,j}(x, y)|^2} \tag{2}$$

where (x, y) is the coordinate, M is the total number of rows and N is the total number of columns of the 2D data. The value of D is usually chosen to be 0.5 to ensure that the mean value of BIMF is close to 0.

Step 10: If $F_{Tj+1}(x, y)$ meets the criteria according to step 9, then $F_j(x, y) = F_{Tj+1}(x, y)$, set $S_{i+1}(x, y) = S_i(x, y)$ and $i = i + 1$, and go to step 11. Otherwise set $j = j + 1$, go to step 3 and continue up to step 10.

Step 11: Determine whether $S_i(x, y)$ has less than three extrema points, and if so, the residual $R(x, y) = S_i(x, y)$, and the decomposition is complete. Otherwise, go to step 2 and continue up to step 11.

In the process of extracting BIMFs, the number of extreme points in $S_{i+1}(x, y)$ should be less than the number of extreme points in $S_i(x, y)$. Let the BIMFs and the residual of a signal together be named as bi-dimensional empirical mode components (BEMCs). All the BEMCs compose the original 2D signal as follow

$$\sum F(x, y) = \sum_{i=1}^{K+1} F_i(x, y) = I(x, y) \tag{3}$$

where $F_i(x, y)$ is the i-th BEMC, and K is the total number of BEMCs except the residual.