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Automated surface texture analysis via Discrete Cosine Transform and Discrete Wavelet Transform

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ABSTRACT

Surface roughness and texture are critical to the functional performance of engineering components. The ability to analyze roughness and texture effectively and efficiently is much needed to ensure surface quality in many surface generation processes, such as machining, surface mechanical treatment, etc. Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) are two commonly used signal decomposition tools for surface roughness and texture analysis. Both methods require selecting a threshold to decompose a given surface into its three main components: form, waviness, and roughness. However, although DWT and DCT are part of the ISO surface finish standards, there exists no systematic guidance on how to compute these thresholds, and they are often manually selected on case by basis. This makes utilizing these methods for studying surfaces dependent on the user's judgment and limits their automation potential. Therefore, we present two automatic threshold selection algorithms based on information theory and signal energy. We use machine learning to validate the success of our algorithms both using simulated surfaces as well as digital microscopy images of machined surfaces. Specifically, we generate feature vectors for each surface area or profile and apply supervised classification. Comparing our results with the heuristic threshold selection approach shows good agreement with mean accuracies as high as 95%. We also compare our results with Gaussian filtering (GF), and show that while GF results for areas can yield slightly higher accuracies, our results outperform GF for surface profiles. We further show that our automatic threshold selection has significant advantages in terms of computational time as evidenced by decreasing the number of mode computations by an order of magnitude compared to the heuristic thresholding for DCT.

1. Introduction

Enhancements in measurement technology have opened the door for applying surface texture analysis to various applications such as medical imaging [1–3], construction materials [4], remote sensing [5,6] and tribology [7,8]. Some of the challenges in surface texture analysis include the data size and the computational effort of some of the current methods. Specifically, as the resolution of the surface images increases, their size also increases, which makes the data processing cumbersome and computationally expensive. Therefore, there is a need for increasing automation and decreasing the computational complexity of algorithms for surface texture analysis. Another challenge is to extract appropriate descriptors for a surface in an automated way. The most common approach used in the literature is to decompose data into form, waviness, and roughness components. This approach is applied to both profiles [9–12] and surfaces [13–15]. The form component includes low-frequency content in the surface or profiles, waviness involves the mid-range frequencies, while the high frequencies are collected in the roughness component. In general, the form and the waviness of a surface scan or profiles are obtained, then they are subtracted from the original data to obtain the roughness component.

Gaussian filter is one of the widely adopted signal processing tools for surface roughness analysis [9,16–19]. It is used to smooth the surface profile measurement to obtain an approximation of the raw surface profile. The mean line is then subtracted from the measurement to obtain a roughness profile. Raja et al. used a Gaussian filter to obtain an approximation to surface profiles, and they compared this approximation with the ones obtained from the 2RC filter, one of the earliest filters used for surface metrology [9]. Hendarto et al. focus on the roughness analysis of wood surface using Gaussian filter [18]. However, the main drawback for Gaussian filtering approach is the boundary distortion where the mean of the end parts of a surface profile cannot be used [9].

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Raja et al. suggested that the end parts of the mean line should be ignored for evaluation [9], while this is not feasible for profiles with shorter lengths. Therefore, Janecki proposed a solution that extrapolates both ends of profiles with polynomial functions to eliminate the edge effect [19]. Another approach used in the analysis of profiles of engineering surfaces is Fast Fourier Transform (FFT). Raja and Radhakrishnan used FFT to obtain the surface roughness by removing the lower frequency components of form and waviness. Dong et al. provide an extensive understanding of two-dimensional FFT (2D-FFT) analysis on engineering surfaces [20]. Peng et al. used 2D-FFT to identify the type of the wear particles on surfaces using angular spectrum values which are obtained by converting Cartesian coordinates into polar form [21]. Empirical Mode Decomposition (EMD), one of the most commonly adopted signal decomposition tools, is another approach used for the analysis of engineering surfaces. Several versions of EMD are proposed to analyze surfaces such as Bidimensional EMD (BEMD) [22], Image EMD (IEMD) [23], Bidimensional Multivariate EMD (BMEMD) [24]. However, the computation of EMD in 2D is slow compared to other approaches.

Discrete Cosine Transform (DCT) is another widely used approach for decomposing a surface scan into its form, waviness, and roughness components [13,14,25,26]. Lecompte et al. developed an approach to identify the form and the contribution of classical defects such as positioning error and tool deflection [13]. They used only a certain percentage of the DCT coefficients to obtain a filtered surface. However, when we have a large number of images, each image may require the usage of a different percentage of the DCT coefficients to generate the form. In general, DCT requires selecting two threshold values for delineating the three different components of the surface.

Discrete Wavelet Transform (DWT) is another approach used extensively for surface texture analysis [9,14,27–33]. Chen et al. introduced DWT for surface profiles [27]. Liu et al. obtained a threshold that isolates the form of the surface by computing all possible approximations that can be obtained using the coefficients at each level. Another example of this approach is seen in Refs. [9,29] where the separation of the three components of a profile is performed using multi-resolution analysis approximations. The common procedure is to apply the DWT at a certain level and obtain the approximation and detail coefficients, and then use the approximation coefficients for the reconstruction of the form component [34]. The detail coefficients are then used to reconstruct waviness and roughness. Nevertheless, there is a need for a guideline on how to automatically choose the threshold that separates the mid-frequency content from the higher ones in the DWT approach. In addition, selection of the mother wavelet function can also affect the resulting components. Stkepien et al. used autocorrelation, cross-correlation, and entropy-based test to evaluate the performance of different wavelet functions used in surface texture analysis [35].

To our knowledge, there is no approach for automatically separating the form, waviness, and roughness components for DCT and DWT, and the current practice is to manually select them using the user's experience and judgment call. Therefore, we propose an automatic, data-driven approach for identifying the needed thresholds for DCT and DWT. For DWT, we utilize the energy of the reconstructed signals to separate the waviness and roughness from each other, while for DCT we leverage the surface entropy to define the form and waviness components. Roughness is then found by subtracting the filtered surface from the original one.

In addition to our contributions to the automatic threshold selection in DCT and DWT, we identify the machining processes through which surface samples are generated. Most studies in the literature are focused on small patch processes with few samples where human interpretation is heavily used to identify and compute profile or surface roughness. In contrast, we validate our approach for a large data set obtained from simulated surfaces, as well as experimental surface scans. We obtain the roughness components of surfaces and profiles using our automatic threshold algorithms and we extract the 1D and 2D features introduced in the ISO standards [36,37]. We then utilize machine learning to assess the accuracy of the automatic thresholds. Specifically, we use the obtained features in supervised classification algorithms to classify surfaces that are labeled with respect to the generating surface parameter for the simulated surfaces, and with respect to the generating machining process for the experimental data. We use support vector machine (SVM), logistic regression (LR), random forest (RF), and gradient boosting (GB) algorithms for classification and employ hyperparameter tuning using the grid search approach.

This article is organized as follows. Section 2.1 provides the details for synthetic surface generation, experimental data collection, and data preprocessing. Section 3 introduces our new automatic threshold selection algorithms and explains how to use them for feature extraction. Section 4 provides classification results obtained using the proposed algorithms and compares them to the results obtained by heuristic threshold selection. We provide our concluding remarks in Sec. 5.

Table 1
Selected surfaces under various machining conditions.

Machining Type	Roughness height (micrometers(microinches))		
M – milling	3.175 (125)	6.35(250)	12.7(500)
P - profiled	3.175 (125)	6.35(250)	12.7(500)
ST - shaped or turned	3.175 (125)	6.35(250)	12.7(500)

2. Data collection

Our data includes both synthetic surfaces (Section 2.1), and digital scans of machined surfaces (Section 2.2. The following subsections provide more information on each data type.

2.1. Synthetic surface generation

We used the model described in Ref. [38] to generate synthetic surfaces. The roughness level of the surfaces is controlled by varying the Hurst exponent H, which takes parameter values between 0 (rough surface) and 1 (smooth surface). We chose 201 different H values in this range, and for each H value we generated a different surface. We then categorized these surfaces with respect to their roughness level. For instance, the first 67 surfaces were labeled smooth, while the last 67 surfaces were considered rough. The surfaces in between these two extremes were considered somewhat rough. The generated surfaces were then used to obtain both areal and profile features. Profiles of the generated surfaces were obtained by taking cross-sections along the generated surface's x and y directions, and they were assigned the same labels as the original surface. Depending on the type of signal processing tool used, we obtained roughness surfaces or roughness surface profiles, and then we extracted the corresponding features needed for the classification algorithms.

2.2. Experimental data collection and preprocessing

A standard S-22 Microfinish Comparator is used for physical surface texture data collection. To better recognize the surface texture, 9 sample surfaces with clearly observed rough texture on the comparator are selected (see Table 1).

The scanned area is 5 mm × 5 mm, and it was consistently located at the upper left corner for each measured sample surface. Specifically, the microfinish comparator was placed on a free-angle XYZ motorized observation system (VHX-S650E), and the surface textures were measured using a Keyence digital microscope (VHX6000), as shown in Fig. 2a. A real zoom lens (Keyence VH-Z500R, RZ x500-x5000) is used to capture the surface texture and × 500 magnification is used to achieve sufficient spatial resolution (0.42 μm). The stitching technique (11 × 11 scans in the horizontal and vertical directions) is performed to enlarge the observation view so that the whole selected area can be captured

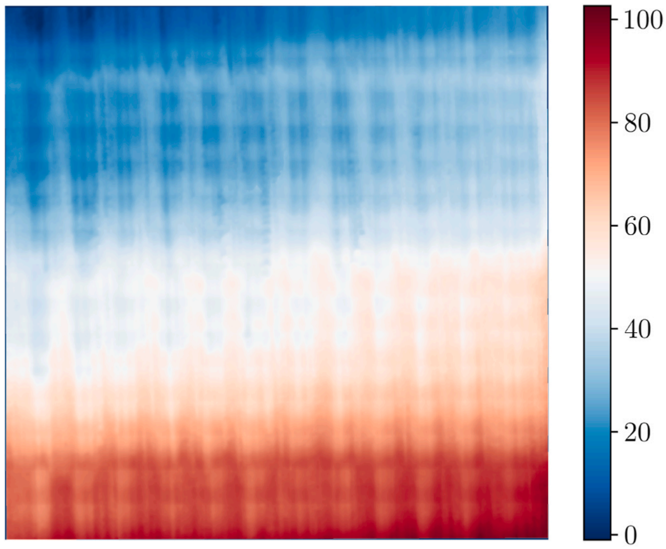


Fig. 1. Scan sample of 125 M.

under this magnification. The spatial sampling rate of the images was approximately 2.4 samples per μm. Fig. 2b shows the resulting scanned surfaces.

2.3. Data preprocessing

The resulting raw surface scans include different numbers of pixels with lower grey-level intensity values on the edges of the image as shown in Fig. 1. These pixels are tedious to isolate manually, so we copped the images and adaptively removed these pixels using the following algorithm. First, we found the remainder of image pixel values in each direction when they are divided by 1000. The halves of the remainders are used as the number of pixels to remove from each edge. This procedure was successful in significantly reducing the number of pixels with lower grey-level intensity values at the boundaries, and the resulting images had similar sizes.

The other challenge was the large dimension of the microscope surface scans which can exceed 10000 pixels in each direction of the image thus elevating computational expenses. Consequently, we split each surface scan into 25 sub-images each with a dimension of 2400 $\times$ 2400 pixels.

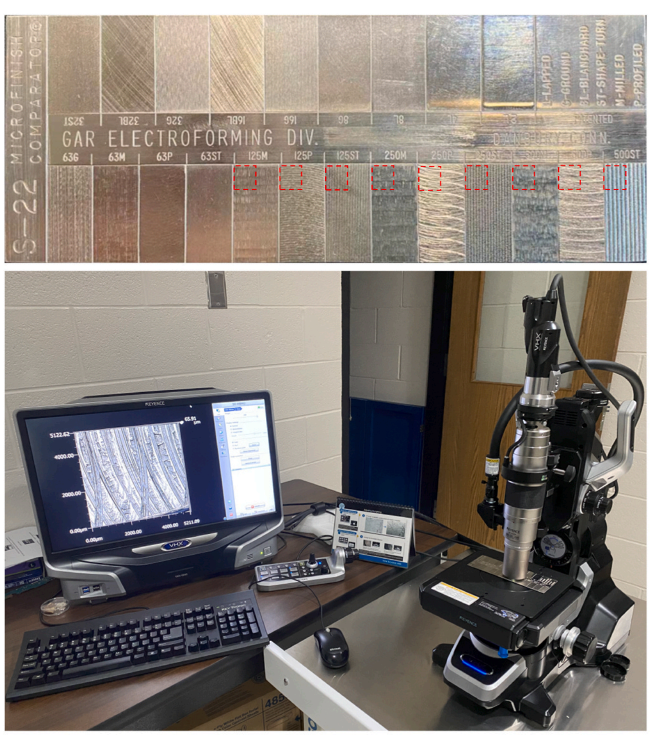
2.3.1. Image subsampling

The resulting subimages still presented computational challenges for some signal processing tools such as DCT where the maximum number of modes is equal to the total number of pixels. Therefore, we subsampled the images to further reduce the number of samples in the subimages when using 2D signal processing tools for surface classification. Several approaches are available for image scaling/resampling in the literature. These also include some signal processing approaches to upscale or downscale an image. One of the simple and widely used subsampling methods is to replace a block of pixels with their average values, and that is the approach we used in this study. After testing different sampling factors such as 0.1, 0.2, and 0.5, we adopted a sampling factor of 0.1 for the experimental data set. This means the size of each block is 10 $\times$ 10 pixels.

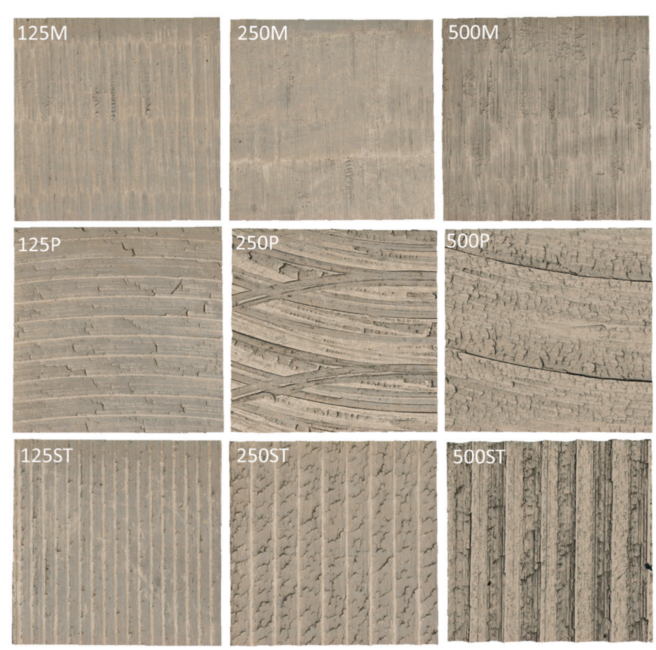
3. Methods

3.1. Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) is one of the widely adopted signal processing tools [39–43]. While a signal's frequency spectrum can only be represented over the entire time domain with Fourier Transform, Wavelet Transform can decompose the signal into components with different time and frequency resolutions [44]. In DWT, the time series is passed through low pass and high pass filters to obtain approximation



(a) Scanned portions of the sample and the digital microscope.



(b) The scanned surface textures.

Fig. 2. The microscope used for experimental data collection, and the sample surfaces.