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Heterogeneous recurrence monitoring of dynamic transients in ultraprecision machining processes

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ABSTRACT

In situ monitoring and control of process variations are important for quality assurance in ultraprecision machining (UPM) processes. Recent advancements in sensing and communication technology have fueled increasing interests to develop sensor-based monitoring approaches for anomaly detection in the UPM process. However, conventional approaches are limited in their ability to address the complex dynamics hidden in the nonlinear and nonstationary processes. As a result, it is difficult for them to effectively capture the process variations of UPM. This paper presents a new heterogeneous recurrence monitoring approach to detect dynamic transients in UPM processes. First, a high-dimensional state space is reconstructed from in situ sensing signals. A Dirichlet process (DP) driven clustering approach is then developed to automatically segment the state space into local recurrence regions. Furthermore, a fractal representation is designed to characterize state transitions among recurrence regions and extract novel measures to quantify heterogeneous recurrence patterns. Finally, we integrate a multivariate control chart with heterogeneous recurrence features for in situ monitoring and predictive control of the UPM process. Experimental results showed that the proposed approach effectively detects transitions with a small magnitude, i.e., $\rho = 28$ to $\rho = 27$ in the Lorenz system, and identifies the shift from stable cutting ($R_a = 35$ nm) to unstable cutting ($R_a = 82$ nm) in UPM processes with an average run length of 1.0. This paper presents a novel data-driven DP clustering approach to characterize heterogeneous recurrence variations and link with the quality of surface finishes in UPM processes. This new DP recurrence approach circumvents the need to empirically define local recurrence regions and is shown to have strong potentials for manufacturing process monitoring and control that will increase the surface integrity and reduce rework rates.

1. Introduction

Rapid advancement of microelectronics and precision manufacturing has fueled the increasing demand of mirror finish surfaces, which have been widely used in diverse industries such as defense and aerospace. Ultraprecision machining (UPM) is a commonly used manufacturing process to generate such optical disks. The UPM is also known as diamond turning and is equipped with a single crystal diamond tool and cyclically cuts nonferrous alloys or composites to generate nanometric surface finish (i.e., surface roughness $R_a < 50$ nm) [1]. As opposed to conventional machining, the depth of cut in UPM is within the range of 2–50 μm, which is of the same order of magnitude as the tool edge [2]. As such, UPM process is exceedingly sensitive to environmental instabilities such as vibrations from nearby machines, temperature variations and inconsistency of material microstructures. A miniature process shift will immediately cause the variations of cutting forces and impact the quality of surface finish, e.g., resulting in large roughness or defects. This, in turn, will waste expensive tools and raw materials and lead to rework. Therefore, increasing yields and reducing costs for UPM hinge on the in situ process monitoring and real-time detection of process shifts.

In the literature, there are increasing interests at the development of data-driven modeling approaches for UPM process control. For example, Takasu et al. [3] focused on the deterioration of surface roughness generated from small vibrations. They developed a model to delineate the relationship between the surface roughness of workpieces and the amplitudes and phases of vibration. Cheung and Lee [4] simulated the three-dimensional topography of machined surface using a limited number of predicted roughness parameters, which helped determine the optimal cutting conditions and setup parameters. However, traditional

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modeling approaches are ineffectual in characterizing complex UPM processes, due to sudden surface finish variations and transient dynamics [1].

This present investigation focuses on advanced sensing technology for real-time monitoring and control of UPM process. As shown in Fig. 1, multiple sensors, including cutting force, vibration and acoustic emission (AE) are installed to extract useful information pertinent to process dynamics in UPM. Notably, in situ assessment of UPM surface integrity has received increasing attention in recent years and is recognized as an emerging research area. For example, Dornfeld et al. [5,6] pointed out the importance of tracking variations in process parameters such as material removal rate and tool conditions using high-frequency sensing. They specifically discussed the application of AE sensors for the monitoring of UPM processes. Bukkapatnam et al. [7] investigated the low-dimensional chaos inherent to the lathe-turning process. Signals from cutting force and AE sensors showed that the turning operation exhibited low-dimensional chaos by the Lyapunov-exponent test.

However, nonlinear dynamics and nonstationary behaviors pose significant challenges on the development of new data-driven approaches for sensor-based monitoring and control of UPM processes. As the UPM process is highly sensitive to the variations of environmental conditions, the distribution of sensor signals is often non-Gaussian, nonlinear and nonstationary [1,2,8]. This, in turn, leads to sudden and sharp variations in the UPM surface morphology. Conventional change-detection approaches are more concerned about linear and Gaussian distributions, and most of them assume the system is in the steady state, i.e., stationary. Furthermore, signals collected from UPM processes are oftentimes contaminated by ambient noises. In other words, the signal-to-noise ratio is low and the frequency spectrum are with broadband characteristics [1]. Hence, traditional signal-processing techniques (e.g., Fourier analysis) are not well suited for analyzing UPM signals. An illustrative example is shown in Fig. 2. It may be noted that the frequency spectrum of vibration signals collected from stable (Fig. 2a) and unstable (Fig. 2b) processes registered similar dominant frequency components (380 Hz and 60 Hz). Also, it is difficult to identify which peak corresponds to the machining process and which one is related to the extraneous factors. Therefore, conventional monitoring approaches are not well suited for capturing complex dynamics hidden in the nonlinear and nonstationary UPM processes.

To address aforementioned challenges, researchers have developed complex models to extract features pertinent to nonlinear

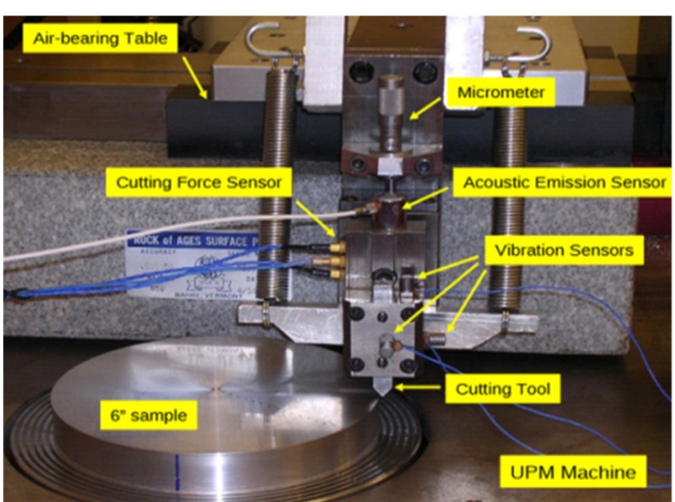

Fig. 1. UPM experimental setup equipped with cutting force, vibration and acoustic emission sensors.

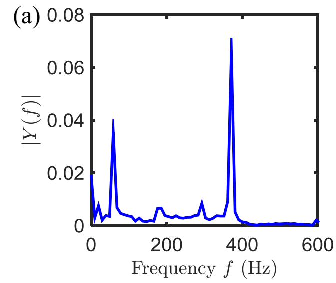

Fig. 2. Frequency spectrum of vibration signals in UPM, with major frequency components at 380 Hz and 60 Hz for (a) stable cutting and (b) unstable cutting.

and nonstationary dynamics in high-precision manufacturing processes. Instead of directly extract statistical patterns of raw signals, Rao et al. [1] utilized neural networks and Bayesian learning for the detection of incipient changes in UPM processes. They extracted the parameters (i.e., weights and biases) of neural network as surrogates to represent process states and further designed Bayesian particle filter to continuously update these parameters based on the observed sensor measurement. Beyca et al. [2] developed a data fusion strategy to integrate heterogeneous in situ sensor signals for the detection of incipient anomalies in UPM processes. In phase I, Bayesian non-parametric Dirichlet process (DP) model was proposed for offline clustering of sensor signals, which were further represented by Gaussian mixture models. In phase II, evidence theory was used for real-time decision-level fusion of newly arrived sensor data. Wang et al. [9] reported a change-point detection method to identify intermittency in UPM processes and chemical mechanical planarization (CMP) processes. The state space of process dynamics was represented by a stochastic mixture of Gaussian clusters. Intra-cluster state evolution was then represented by a nonlinear stationary process and inter-cluster transitions were captured by a Markov model. Recently, Rao et al. [10] proposed a graphical approach for the quantification of UPM surface variations. Instead of using 1-D signals, this method constructed a graph from microscopic surface images. Representative features (i.e., Fiedler number) were extracted from the graph for the detection of defects such as pits, ridges, and scratches.

It may be noted that nonlinear recurrence behaviors are common in real-world complex systems and have been widely used for the detection of process anomalies [11,12]. Fig. 3 demonstrates 2D state space attractors extracted from vibration signals and corresponding recurrence plots for both stable (Fig. 3a and b) and unstable (Fig. 3c and d) UPM processes. Notably, Fig. 3a shows a clear periodic circular trajectory but the attractor shown in Fig. 3c is relatively chaotic. As a result, recurrence plots in Fig. 3b and d show distinct patterns. Recent investigations have shown that recurrence quantification analysis is an effective tool for characterizing nonlinear and nonstationary dynamics [13,14]. However, most of existing works focus on homogeneous recurrence analysis that characterize all recurring states in the same way using a Heaviside function. If the proximity of two states is greater than a predetermined threshold, it is color coded as a black dot in the recurrence plot. Otherwise, it is coded as white. As such, a black-and-white recurrence plot is obtained with black dots representing recurring states (see Fig. 3b and d). Nevertheless, recurrence states may be heterogeneous (i.e., different types of recurrence behaviors) due to state properties, neighboring states and the evolving system dynamics [15,16]. The intermittency and transient changes induced by underlying process shifts are more concerned with heterogeneous recurrence variations in the sensor signals. However, homogeneous recurrence analysis is limited in the ability to fully discern different kinds of recurrence behaviors in the UPM process.