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A sensor-based analytic approach for predictions of nanomachined surface profile variations via capturing temporal-spectral Acoustic Emission (AE) features for vibration-assisted Atomic Force Microscopic (AFM) based nanopatterning

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ABSTRACT

The atomic force microscope (AFM)-based nanomachining has the potential for highly customized nanofabrication due to its low cost and tunability. However, the low productivity and issues related to the quality assurance for AFM-based nanomachining impede it from large-scale production due to the extensive experimental study for turning process parameters with time-consuming offline characterizations. This work reports an analytic approach to capturing the AE spectral frequency responses from the nanopatterning process using vibration-assisted AFM-based nanomachining. The experimental case study suggests the presented approach allows characterizations of subtle variations on the AE frequency responses during the nanomachining processes (with overall 93% accuracy), which opens up the chance to explain the variations of the nano-dynamics using the senor-based monitoring approach for vibration-assisted AFM-based nanomachining.

Keywords: AFM-based Nanomachining, sensor-based monitoring, ensemble tree regression

1. INTRODUCTION

Nanofabrication gains attraction among researchers and industry in bio-production, nanolithography, and semiconductor sectors [1]–[3]. The atomic force microscope (AFM) based nanomachining process has excellent tunability for customized nanopatterning with low lost setup and high-quality finishes [4] for various methods of performing nanofabrication [5]–[8]. During the AFM-based nanomachining process, the issues on the quality integrity are critical due to the influence of the uncertainty of the tool-tip and surface geometry variations during the process: the tool-tip radius, system vibrations, and the material microstructures are within the same order of magnitude; any variations during the process will create the changes on the material removals and therefore influence the achieved surface integrity. The characterizations of nanomachined products require offline measurement and inspections; particularly, the visualization of the achieved surface finish is difficult as the geometry of the surface finish is within the nanoscale, where the optical measurement tools lose their capability under such a dimension. The achieved surface characteristics can only be measured by the AFM setup itself [9], which is offline and consequently cannot provide instantaneous feedback of the surface quality during the machining. As a result, this brings up the productivity and product reliability issues that impede the current production of AFM-based nanomachining from wide applications [10]. Therefore, it is necessary to provide an in-process monitoring approach to capture subtle changes during the process to reduce the extensive characterization phase and allow real-time diagnosis and timely intervention for quality assurance.

This work extends from the previously presented in-process sensor-based monitoring scheme on nanomachining [11]. It explores the capability of capturing subtle anomalies/variations of the nanomachining process using the presented setup. The established sensor setup applies the acoustic emission (AE) sensor, which gathers the transient elastic waves generated from the energy releases during the material removals [12]. The ensemble tree regression (ETR) model is proposed to capture the frequency components variations of AE responses. The results suggest that the currently employed ensemble learning-based regression model can accurately capture the variations of AE frequency responses related to subtle changes in the nanomachining. The experimental case study shows improvements compared to previous results on predicting the surface profile. The remainder of this paper is organized as follows: Sec. 2 presents the experiment setup and collected data for the vibration-assisted AFM-based nanomachining process. The employed ensemble learning-based approach that captures the variations of the machining process via the AE sensor-based monitoring scheme is reported in Sec. 3. Sec. 4 presents the results of the experimental case study followed by discussions. Sec. 5 concludes this paper.

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2. EXPERIMENTS AND DATA DESCRIPTION

2.1 Experimental setup

The nanomachining experiments were conducted on a customized vibration-assisted AFM-based nanomachining platform (see Figure 1). The AFM system is from Park systems Corporation (XE7, Park Systems). The nano-vibrator stage with two piezoelectric actuators is installed on the bottom of the sample holder aluminum pillar (see Figure 1) to allow the system vibrations in xy-plane for nanopatterning. The vibrations of the nano-vibrator stage are generated by a signal generator (USB-6259, National Instruments) and two signal amplifiers (PX200 from PiezoDrive) through the piezoelectric actuators with the intrinsic frequency of 2 kHz on the sample plate. The polymethyl methacrylate (PMMA) samples are mounted on the sample holder, and processed by the AFM probe (DLC190). During the machining, the AE sensor (s9225 from Physical Acoustics) is installed in the systems and gathers the information at a sampling rate of 500 kHz using the data acquisition systems (DAQ) from National instruments (NI-USB-6259).

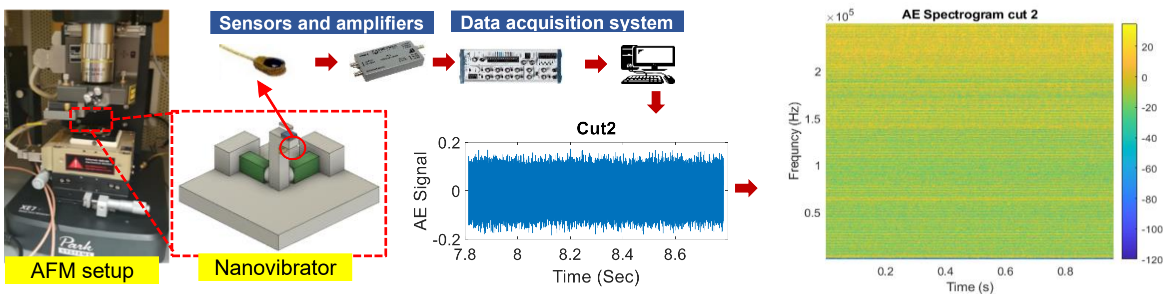

Figure 1. The customized AFM platform with equipped AE sensor and DAQ system with an exemplary AE sensor signal and the transformed temporal-spectral diagram showing the time-varying nature of the AE signals during the nanomachining process.

2.2 Experiment data observations

A set of experiments was conducted on the presented setup with different machining down forces (50, 150, 250, 350, and 450 nNs) on machining a PMMA sample surface with a cutting length ~1 μm. Each experiment condition was repeated twice, and the information generated during the process, including the AE signals, downforce signals, and lateral signals were synchronously collected. Figure 2 illustrates the nanomachined surface of the PMMA sample under different cutting forces. It may be noticed that the depth of the machined surface profile is within 20 nm.

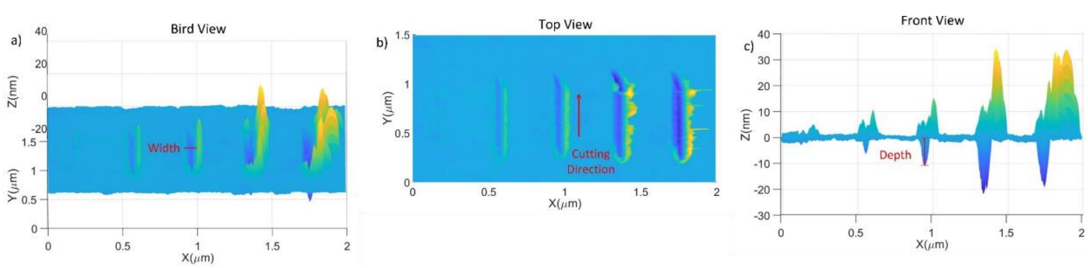

Figure 2. The visualizations of the machined nanotrenches based on offline AFM characterizations from different views. In total, five trenches are machined based on different cutting forces (50, 150, 250, 350, and 450 nNs).

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3. DATA ANALYTICS AND RESULT DISCUSSIONS

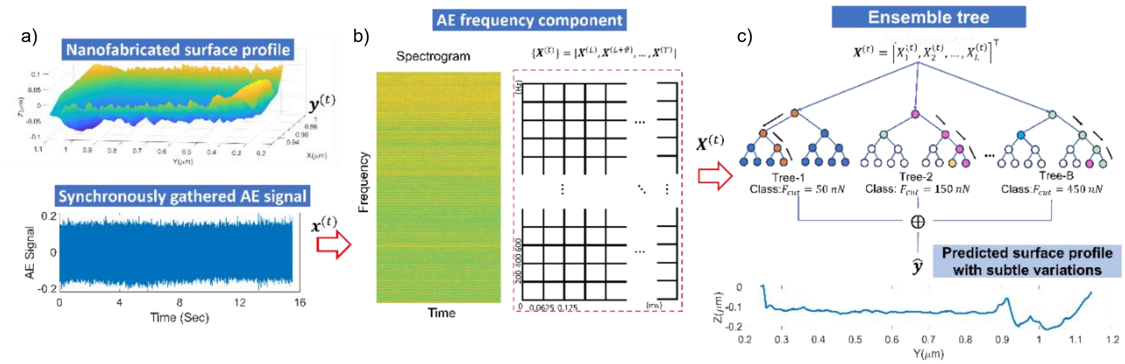

Figure 3. The schematic diagram for the sensor-based monitoring scheme on tracking the nanomachining process: a) the synchronously gathered AE sensor signals capture the AE information during the machining of nano trench; b) the windowed FFT transformation generates the temporal-spectral features of AE signals, which is treated as the inputs for the ensemble learning based prediction model in c) to capture variations of the AE responses in real-time and estimate the surface profile in the nanoscale.

The schematic diagram of the presented analytic approach is shown in Figure 3. During the nanomachining, the DAQ system collects the AE signals with synchronously gathered downforce information. The change of the downforce signals can be the indicator of the cutting initiation and thereby locate the AE signal segments during the nanomachining to the machined surface profile.

The collected AE signal during the nanomachining process can be formulated as a time series $\{x_t\}$ with the time interval $\Delta t = 1/Fs$, where Fs is the sampling rate of the DAQ system. In this experimental setup, $Fs = 500\text{kHz}$ and $\Delta t = 1\mu s$. The streaming data $\{x_t\}$ is then treated with the Fast Fourier Transformation (FFT) for generating temporal-spectral features: given a sliding window with window size N (the window length N=5000, i.e., the time duration of 10 milliseconds), the spectral components of the windowed signal $\{x_{t-N+1}, x_{t-N+2}, \ldots, x_t\}$ can be formulated as

$$X_k^{(t)} = \sum_{n=t-N+1}^{t} x_n e^{-\frac{i2\pi kn}{N}} \quad k = 0, \ldots, N-1 \tag{1}$$

where x_n is the temporal AE signal which can be represented as $\{x_n, n = t-N+1, t-N+2, \ldots t\}$ in a sliding window, the transformed frequency components is represented as $\boldsymbol{X}^{(t)} = \left[X_1^{(t)}, X_2^{(t)}, \ldots, X_N^{(t)}\right]^{\top}$. Based on the sliding window, a sequence of the spectral features $\boldsymbol{R} = \{\boldsymbol{X}^{(t)}\} = [\boldsymbol{X}^{(N)}, \boldsymbol{X}^{(N+S)}, \ldots, \boldsymbol{X}^{(M)}]$ can be generated, where S is the step of the sliding window for $t = N \ to \ M$. $\boldsymbol{R}$ essentially the magnitudes of each Fourier transformed components for $\{\boldsymbol{x}_t\}$, which shapes the spectrogram as suggested in Figure 3 b).

This paper reports an analytic model that captures the AE temporal-spectral features and relates them to the resultant material removed during the nanomachining. The cutting depths $\boldsymbol{y}_t$'s are used as the responses in the prediction model and the corresponding spectral features $\boldsymbol{X}^{(t)}$ for the prediction model. The ensemble tree regression model establishes the relationship between surface profile feature $\boldsymbol{y}_t$ and spectral features $\boldsymbol{X}^{(t)}$. The regression tree model [13] can be formulated as follows:

$$f\left(\boldsymbol{X}^{(t)}\right) = \sum_{i=1}^{\mathbb{D}} \beta_i \times I(X_i^{(t)} \in \mathcal{D}_i) \tag{2}$$

where β_i is the coefficients for the predictors $X_i^{(t)}$, $I(\cdot)$ is the indicator function returning 1 if its argument is true and 0 otherwise. The disjoint partitions $\mathcal{D}_i$'s follow the conditions such that $\cup_i^{\mathbb{D}} \mathcal{D}_i = \mathcal{X}$ and $\cap_i^{\mathbb{D}} \mathcal{D}_i = \phi$, and $\mathcal{X}$ is the space given all the observations of $\boldsymbol{X}$'s. Essentially, this approach partitions finite $\mathbb{D}$ regions in the predictor space $\mathcal{X}$ and estimates the coefficients β_i therein for the prediction.

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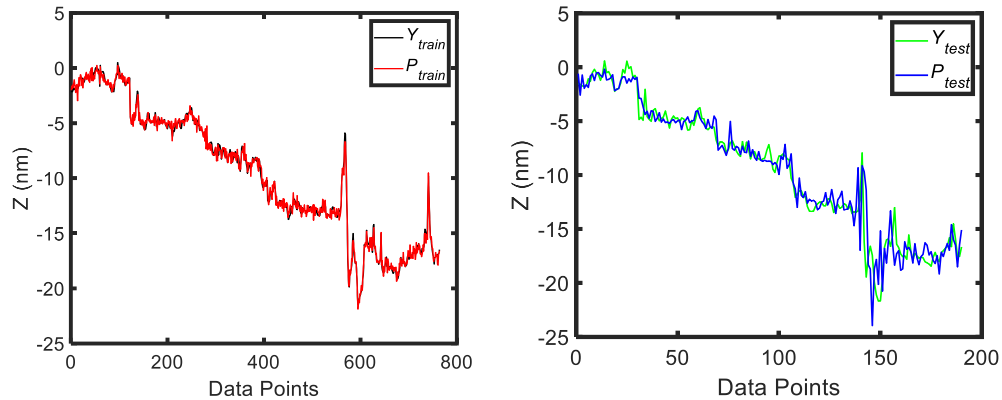

Figure 4. Prediction results using Ensemble Tree Regression (ETR): a) the training data set with the prediction results (red as the predicted values and the black line is the ground truth/ observations); b) the collection of the surface profile (cutting depth data) with the prediction results (blue line) vs. the ground truth of the testing set (in green).

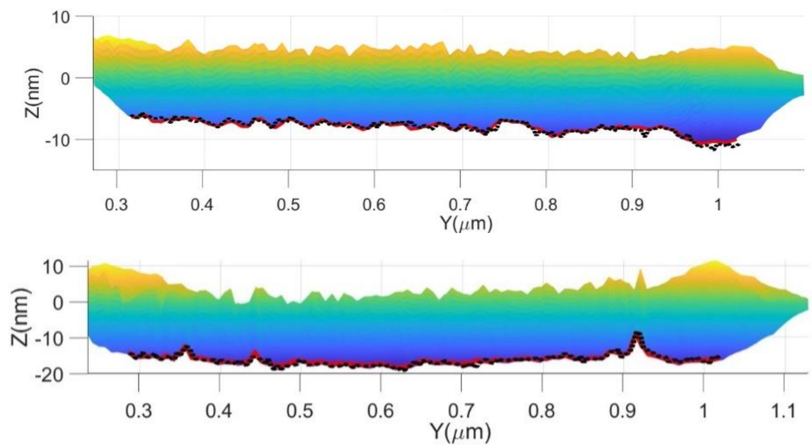

Figure 5. The result comparisons between the ground truth (surface profile in the color map and the surface depth in the red line) and predicted depth profile plotted in black dash line.

To test the performance of the prediction model, the surface profiles extracted from five cuts are used as the responses for the prediction model, and the corresponding temporal-spectral features of the AE signals are used as the predictors for the ensemble tree regression model. All frequency features of the five cuts are separated into two groups —80% for training data and 20% for testing—and the R-squared and RMSE (root-mean-square deviation) metrics are used to evaluate the prediction performance.

The ground truth of the profile depth and the predicted depths for the training and the testing data are shown in Figure 4: the black line (Y_{train}) represents the ground truth of the cutting depths, and the red line depicts the predicted cutting depths (P_{train}); the green line (Y_{test}) and the blue one (P_{test}) are the ground truth and the predicted values for the testing data. It may be noticed that the ETR approach can properly capture the variations on the surface profile. Based on the observations from the surface morphology in Figure 2, these variations on the machined surface may be highly related to subtle changes during the nanomachining.

As for both the training and testing phases, the prediction model obtained a high R-squared value, indicating that the AE frequency bands can explain around 93 % variation of the cutting depths (see Table 1). In addition, the RMSE achieves a mean of 0.0014 based on ten computations, which verifies that the approach is stable for inferencing the machined profiles based on AE signals. As suggested in Figures 4 a) and b), the predicted surface profile values (in red and blue, respectively) highly conform to the ground truth. In addition, we compare the prediction results with the ground truth for exemplary surface profiles (see Figure 5), where the red line is the predicted profile and the black line is the experimental observation. These suggest that the AE -sensor-based ETR prediction model can properly capture the variations during the machining and allows accurate prediction on the nanomachined surface profiles.

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Table 1. A summary of the prediction results in terms of R-squared and RMSE values.

	Q1	Q2	Q3	Q4	Variance	Mean
R-squared	0.9234	0.9304	0.9507	0.9573	0.0001	0.9396
RMSE	0.0012	0.0013	0.0015	0.0016	0.0000	0.0014

4. CONCLUSIONS

In this paper, an ensemble learning-based prediction approach is integrated with the AE sensor-based monitoring scheme to capture the temporal-spectral variations of AE signals during the nanomachining. Investigations suggest that the presented framework can estimate the surface profile in real time by discerning the subtle changes in the information contained in AE signals. In the future, the robustness of the presented approach needs to be investigated given high dimensional temporal-spectral features from AE signals.

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REFERENCES

[1] P. T. Mathew, B. J. Rodriguez, and F. Fang, “Atomic and Close-to-Atomic Scale Manufacturing: A Review on Atomic Layer Removal Methods Using Atomic Force Microscopy,” *Nanomanuf Metrol*, vol. 3, no. 3, pp. 167–186, Sep. 2020, doi: 10.1007/s41871-020-00067-2.

[2] I. Ortlepp *et al.*, “Nanofabrication and -metrology by using the nanofabrication machine (NFM-100),” in *Novel Patterning Technologies 2022*, San Jose, United States, May 2022, p. 30. doi: 10.1117/12.2615118.

[3] B. Yao, C. Chen, Z. Du, Q. Qian, and L. Pan, “Surfing Scanning Probe Nanolithography at Meters Per Second,” *Nano Lett.*, vol. 22, no. 6, pp. 2187–2193, Mar. 2022, doi: 10.1021/acs.nanolett.1c03705.

[4] Q. Tang, S.-Q. Shi, and L. Zhou, “Nanofabrication with Atomic Force Microscopy,” *Journal of Nanoscience and Nanotechnology*, vol. 4, no. 8, pp. 948–963, Nov. 2004, doi: 10.1166/jnn.2004.131.

[5] J. Deng, J. Dong, and P. H. Cohen, “Development and Characterization of Ultrasonic Vibration Assisted Nanomachining Process for Three-Dimensional Nanofabrication,” *IEEE Trans. Nanotechnology*, vol. 17, no. 3, pp. 559–566, May 2018, doi: 10.1109/TNANO.2018.2826841.

[6] X. Zheng *et al.*, “Patterning metal contacts on monolayer MoS2 with vanishing Schottky barriers using thermal nanolithography,” *Nat Electron*, vol. 2, no. 1, Art. no. 1, Jan. 2019, doi: 10.1038/s41928-018-0191-0.

[7] Y. Tian *et al.*, “Design of a novel 3D tip-based nanofabrication system with high precision depth control capability,” *International Journal of Mechanical Sciences*, vol. 169, p. 105328, Mar. 2020, doi: 10.1016/j.ijmecsci.2019.105328.

[8] J. Stauffenberg *et al.*, “Investigations on Long-Range AFM Scans Using a Nanofabrication Machine (NFM-100),” in *4th International Conference nanoFIS 2020 - Functional Integrated nanoSystems*, Dec. 2020, p. 34. doi: 10.3390/proceedings2020056034.

[9] H. Zhou, Y. Jiang, C. M. Dmuchowski, C. Ke, and J. Deng, “Electric-Field-Assisted Contact Mode Atomic Force Microscope-Based Nanolithography With Low Stiffness Conductive Probes,” *Journal of Micro and Nano-Manufacturing*, vol. 10, no. 1, Apr. 2022, doi: 10.1115/1.4054316.

[10] A. A. Tseng, “Advancements and challenges in development of atomic force microscopy for nanofabrication,” *Nano Today*, vol. 6, no. 5, pp. 493–509, Oct. 2011, doi: 10.1016/j.nantod.2011.08.003.

[11] Q. Ma, H. Zhou, J. Deng, and Z. Wang, “Characterizing vibration-assisted atomic force microscopy (AFM)-based nanomachining via perception of acoustic emission phenomena using a sensor-based real-time monitoring approach,” *Manufacturing Letters*, vol. 34, pp. 6–11, Oct. 2022, doi: 10.1016/j.mfglet.2022.08.009.

[12] Z. Wang *et al.*, “Characterization of the physical origins of acoustic emission (AE) from natural fiber reinforced polymers (NFRPs) machining processes,” *Int J Adv Manuf Technol*, Sep. 2021, doi: 10.1007/s00170-021-07956-w.

[13] L. F. R. A. Torgo, “Inductive learning of tree-based regression models,” 1999, Accessed: Feb. 28, 2023. [Online]. Available: https://repositorio-aberto.up.pt/handle/10216/10018

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