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SIGNAL-BASED SURFACE QUALITY ASSESSMENT IN MANUFACTURING

Ismail BOGREKCI, Pinar DEMIRCIOGLU

Abstract: *This study investigates surface quality assessment in machining through signal processing techniques, focusing on Fast Fourier Transform (FFT) and Wavelet Transform (WT). The signals, extracted from confocal microscope images through the utilization of Matlab's signal processing toolbox. This study explored the effectiveness of FFT and WT for evaluating surface roughness, employing coarse, medium, and fine surfaces as sample materials. The roughness signals from these surfaces were subjected to FFT and WT processing, revealing the feasibility of using these techniques for surface roughness assessment. A performance evaluation compared these methods to determine the most suitable technique for discerning surface topography. The findings enhance the comprehension of surface quality assessment, providing valuable insights for selecting optimal methodologies tailored to specific applications.*
Key words: *Manufacturing, Surface Metrology, Fast Fourier Transform (FFT), Wavelet Transform (WT), Signal Processing*

1. INTRODUCTION

Machine part surfaces often exhibit irregularities, such as surface roughness, stemming from manufacturing processes. Surface roughness is a crucial parameter describing surface texture, impacting various aspects like contact pressure, preload loss, wear properties, coating properties, fatigue strength, adhesive-bonded joint strength, and frictional losses in fluid systems. ISO 21920-2:2021 defines surface roughness measurement with parameters like Ra and Rz. Ra, commonly used for general surface texture assessment, may lose sensitivity with sudden amplitude fluctuations. Rz, considering the five highest peaks and valleys, is preferred for sensitivity in such cases. This study aims to correlate acoustic measurements with surface roughness, evaluating Ra for general condition and Rz for sensitivity. Both parameters are considered for their relevance to acoustic measurement values [1].

Surface roughness measurements can be contact or noncontact [2-4]. Stylus profilometry, a contact method, involves moving a diamond tip over the surface. Noncontact methods, like laser profilometry, optically monitor surfaces, relying on laser beam intensity and material surface brightness to map the surface roughness profile. Laser profilometry is a highly favored noncontact method, especially when the measured surface is exposed and accessible.

In mechanical engineering, surface roughness investigations are a major area of concentration [5]. Achieving high-quality surface roughness in manufacturing by minimizing production time and adjusting machining parameters online is a feasible goal [6]. Efforts to enhance surface texture and estimate optimal machining conditions face challenges due to numerous influential variables. These efforts often involve image processing on the manufactured surface and analysis of cutting parameters. Unfortunately, many image processing methods [7] primarily operate offline. Despite this limitation, methods like the one proposed by Pour [8] show promise in advancing online surface quality optimization in machining processes. The methods discussed involve analyzing latent information in image pixels. In the latter category, Misaka et al. utilized Kriging

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and Co-Kriging methods for robust surface roughness prediction from cutting tool vibration signals [9]. Reference [10] further advances by proposing time-series analyses for predicting future vibration signals. Despite efforts using specialized equipment in simulating machining processes, Misaka et al.'s methods address challenges with insufficient training data, and the cost-effective use of a camera for surface roughness control has increased focus on image-based methods.

In machining processes, surface roughness is influenced by a multitude of parameters, including cutting depth, progress rate, cutting speed, tool material, vibrations, clamping torque, workpiece temperature, tool contact conditions, spindle speed, feed rate, lubrication, tool geometry, and machining strategy. Extracting surface roughness conditions is vital for real-time control and optimization of cutting parameters [11]. International standards like ISO 4287 and DIN 4768 define surface roughness using criteria like Ra, Rz, Rt, and Rmr. This paper focuses on evaluating Ra, a widely used parameter in previous research and industrial designs, defined by Equation (1).

$$Ra = \frac{1}{l_r}\int_0^{l_r} \left| z(x) \right| dx \tag{1}$$

where is z(x) is the profile deviation from the mean line and lr is the sampling length.

The surface texture parameter serves the purpose of assigning a quantitative value to articulate the characteristics of a portion of a surface. Its primary functions include facilitating comparisons between different surface areas and establishing a measurable criterion within the production quality system. The assessment of surfaces heavily relies on the concepts of "peaks" and "valleys," which delineate the highest and lowest points, respectively. In accordance with established standards, a profile element is defined as comprising both a peak and a valley. Specifically outlined in ISO 3274 (2017) and ISO 4287 (2015) (refer to Figure 1), a profile element represents a segment of a surface profile. This segment spans from the point at which it intersects the mean line to the subsequent intersection in the same direction. These standards provide a systematic framework for measuring and characterizing surface features, ensuring a standardized approach to surface texture evaluation.

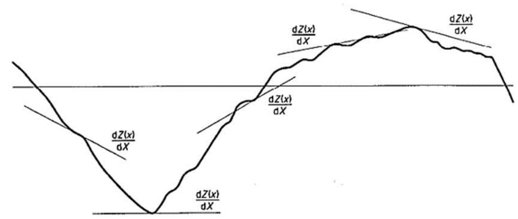

Fig. 1. Profile element

The capital letter in the parameter symbol defines the type of profile for evaluation (e.g., Ra for roughness, Wa for waviness, Pa for primary). 2D surface measurement has limitations in surface inspection as it may not reveal the functionality of the surface, leading to difficulties in accurately determining topographical features. Areal surface characterization, in contrast, provides a more comprehensive understanding without the need for distinct groups, enhancing insights into surface features and properties.

2. SIGNAL PROCESSING & ANALYSIS

The rapid advancement of Digital Signal Processors (DSPs) has facilitated the application of complex DSP techniques, making them more accessible and practical. DSP can be implemented through software or hardware, and the software-based approach proves cost-effective for research purposes. This involves digitizing signals at a rate at least twice the system's natural frequency, and specific signal analysis techniques are developed accordingly. DSPs and associated circuits play a vital role in measurement and control applications, enhancing system efficiency and cost-effectiveness.

Signal processing techniques cover a range of methods, broadly categorized into signal analysis/feature extraction and signal filtering/shaping. Examples include speaker recognition, target identification, noise removal, and spectral analysis. Practical DSP systems integrate various components and techniques, such as digital filtering, frequency determination, spectral analyses using methods like FFT and WT, frequency determination with signal pattern recognition, cross-correlation, and statistical signal processing involving mean, standard deviation, and RMS.

3. MATERIALS AND METHOD

In contemporary manufacturing, achieving the appropriate surface finish is vital for meeting product performance standards, optimizing functionality, and enhancing aesthetics. Previous experiments involved specimens from diverse machining processes, with Figure 2 depicting surfaces having roughness values of 0.498μm, 2.382μm, and 3.984μm (Ra), computed as the average of ten consecutive measurements. These roughness values offer crucial insights into specimen surface quality, playing a critical role in quality control and optimization within manufacturing processes. The ten consecutive measurements for each roughness value contribute to statistical robustness, offering reliable insights. The findings not only inform quality control measures but also play a key role in optimizing manufacturing processes for enhanced product performance and aesthetics. As the manufacturing landscape continues to evolve, such investigations contribute to the surface finishing techniques, aligning products with the highest standards and end-user expectations.

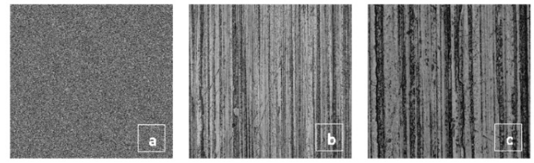

Fig. 2. Visual Inspection of Workpiece Surfaces: a) Ground (Ra=0.498μm), b) Front Milled (Ra=2.382μm), and c) Face Turned (Ra=3.984μm) [3], [7], [12], [13]

4. RESULTS

The signals, extracted from NanoFocus confocal microscope images, underwent processing using Matlab's signal processing toolbox, renowned for its robust mathematical, signal, and image processing capabilities. The authors devised four specialized programs to carry out essential tasks such as FFT, WT, and computation of amplitude and frequency for the signals. Using FFT, the study delved into revealing the frequency distribution, a critical factor in determining surface roughness and topography parameters. Additionally, the research rigorously evaluates the performance of fundamental wavelets, including Haar, Daubechies, and Symlets, in achieving optimal wavelet transformations. Beyond these comprehensive analyses, the paper intricately computes the values for both amplitude and frequency of the signals, providing a detailed exploration of the signal characteristics and contributing to an understanding of the underlying surface features.

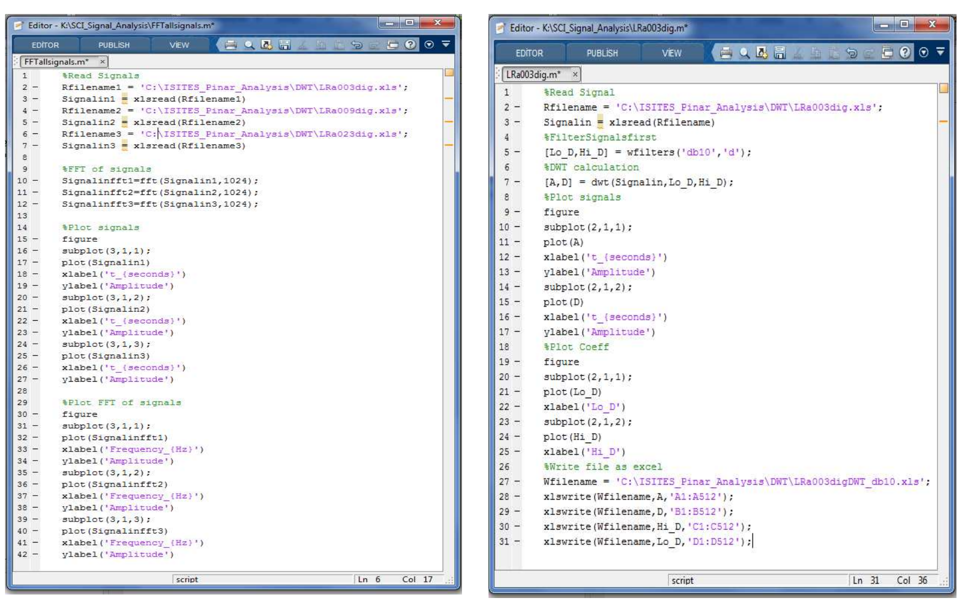

Fig. 3. Matlab programs - FFT (left), and WT (right)

The Matlab programs showcased in Figure 3 serve as powerful tools for FFT and WT analyses. Specifically engineered to handle signal processing tasks, these programs exhibit functionality in reading signals from a file, executing both FFT and WT analyses, visualizing the results through plots, and systematically recording the outcomes along with the processed signals into a file. This streamlined process not only enhances the efficiency of the analyses but also ensures a well-documented and organized approach to handling and storing the valuable information derived from these signal processing techniques. The detailed implementation depicted in Figure 3 contributes to the reproducibility and clarity of the analysis, providing researchers with a robust framework for examining and interpreting the results of FFT and WT analyses.

4.1 Surface Measurement Results and Evaluation

The implementation of this study involves two distinct steps. The first step entails conducting roughness measurements using the NanoFocus confocal microscope (Figure 4). In this phase, the surface characteristics are captured and quantified, providing essential data for further analysis. The second step focuses on the analysis of the captured images utilizing the proposed signal processing techniques. This involves applying advanced methods, potentially including FFT and WT, to extract valuable information from the acquired images. These complementary steps, involving precise measurement and signal processing, collectively contribute to a comprehensive understanding of surface roughness characteristics and enhance the study's overall analytical depth.

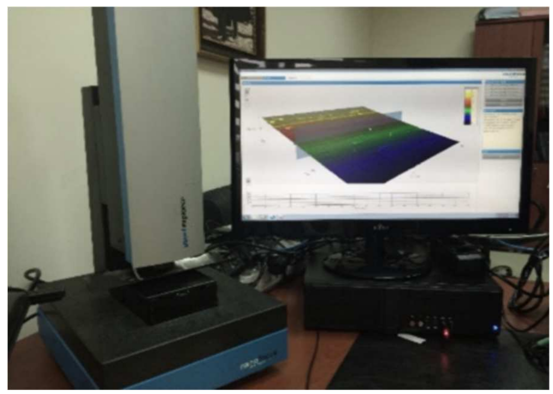

Fig. 4. Confocal Microscope

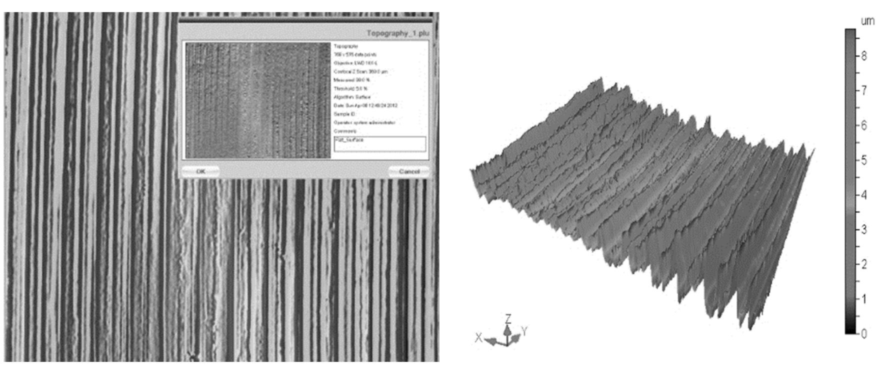

Fig. 5. Surface topography of flat surface in 2D (left) and 3D (right)

Figure 5 provides an overview of the topography of a flat surface featuring an identity card that includes pertinent information such as the number of data points, objective utilized, confocal scan range, measurement performance, threshold, algorithm, as well as the sample name and date. In this specific measurement, the performance achieved was an impressive 99%. The data point resolution, confocal scan range, and objective used were 768 x 576 points, 360 µm, and LWD 10 x-L, respectively (confocal objective). Moving on to Figure 5, it displays the confocal image of the sample captured using a monochromatic blue LED light source, confocal objective, and the confocal option selected. The confocal technique, meaning "with the focus," results in bright points on the focal plane, while others remain dark, providing a detailed representation of the surface topography.

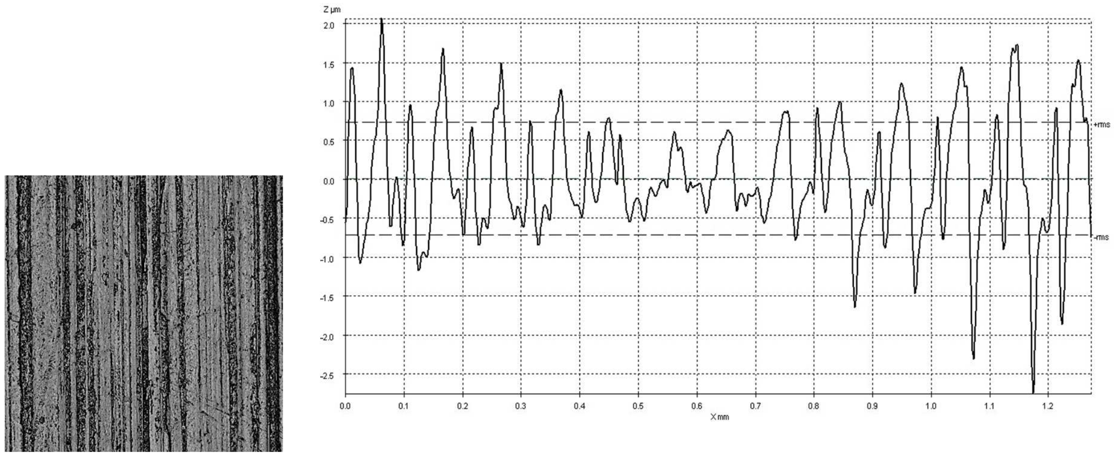

Fig. 6. Confocal image of flat surface (left), Roughness profile of the selected area of the flat surface (right)

4.2 Signal Analysis Results and Evaluation

Filtering is a transformative process applied to a profile or surface to eliminate components of surface relief that are deemed irrelevant for measurement analysis. It's not just a technical step; it's a smart move to make the data better. By removing unnecessary details and highlighting the important roughness features, the filtered profile becomes a clean canvas for meaningful insights. The cut-off, often referred to as the wavelength threshold, segregates large wavelengths above the cut-off as waviness and small wavelengths below the cut-off as roughness. Filtration involving short wavelengths (or high frequencies) is specifically employed for profiling roughness. In the presented case, the roughness profile (Figure 6) was derived by utilizing a Gaussian filter with a cut-off set at 0.8 mm. This filtering operation serves to enhance the focus on surface roughness features, contributing to a refined and more meaningful analysis of the measurement data.

In the previous study [3], the measured workpieces were of dimensions 5x5 mm, and the field view of the instruments covered an area of 21x21 μm. Each measurement was based on the average of six scans, ensuring a robust and representative dataset. The inclusion of eleven roughness parameters in each measurement emphasizes the thorough scope of the study, offering a comprehensive perspective on surface characteristics. Concentrating particularly on Ra values, recognised for their broad applicability in surface quality assessment, the study investigates the detailed aspects of machined surfaces. This multi-parameter approach not only deepens the understanding of surface features but also establishes a foundation for thorough analyses and comparisons in the context of surface roughness.

The results of signal analyses were displayed alongside Ra values, and Figure 7 visually shows signals linked to smooth, medium, and coarse surface conditions. This comparison serves as a robust method to assess the effectiveness and accuracy of signal-based surface quality assessment compared to conventional Ra measurements. The visual representation in Figure 7 offers valuable insights into the varied signals across different surface textures. This contributes to a better understanding of the intricate correlation between signal characteristics and traditional roughness parameters, promoting a more in-depth exploration of surface quality in machining processes. This visual exploration enhances our ability to detect subtle distinctions in surface textures, ultimately refining our grasp of how signal features intricately relate to established roughness measures in the context of machining processes. This comprehensive approach not only broadens the insights into machined surfaces but also lays the groundwork for an understanding of how different parameters collectively contribute to the assessment of surface quality.

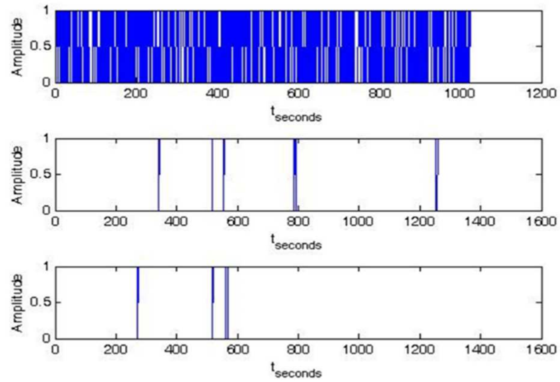

Fig. 7. The signals of smooth (upper), medium (center), coarse (lower) surfaces

The Fourier Transform is contributory in detecting frequency components for surface roughness analysis. Time series signals contain valuable information about surface characteristics, particularly geometric attributes. By decomposing the signal into sinusoidal components in the Fourier domain, specific frequencies within the signal can be examined or processed. Utilizing the 1D FFT function in Matlab, the transformation of time series into the frequency domain is facilitated, enabling the identification of significant factors influencing surface roughness. This approach enhances the analysis of surface features, offering a detailed understanding of the signal's frequency components and their correlation with surface characteristics.

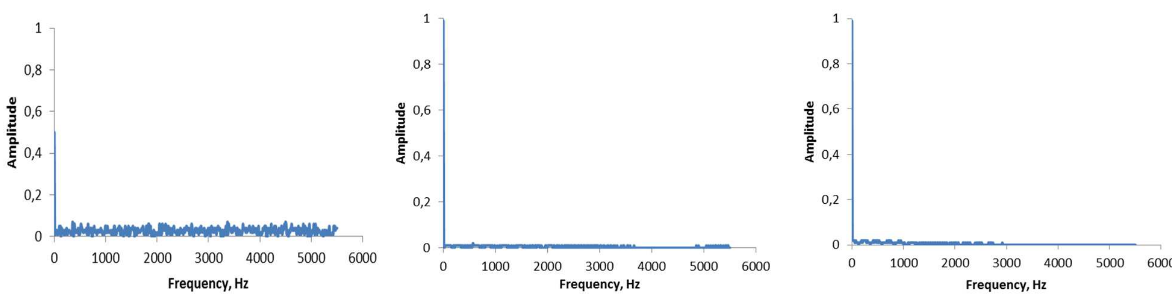

Fig. 8. The signals of smooth (left), medium (center), coarse (right) surfaces after FFT analyses

Figure 8, the signals corresponding to smooth, medium, and coarse surfaces are analyzed using FFT. The distinctive frequency patterns observed for each surface type provide valuable insights. Smooth surfaces exhibit higher frequencies, concentrated between 0 and 5500 Hz, indicating a finer texture. In contrast, coarse surfaces generate lower frequencies with low amplitudes, primarily between 0 and 3000 Hz, reflecting a rougher texture. Medium surfaces display a combination of scattered high and low frequencies with low amplitudes, showcasing an intermediate roughness profile.

The study extends its investigation to surface roughness using a comprehensive approach involving image and signal processing techniques. Images captured at the same location are processed and analyzed using Matlab's image/signal processing toolbox. The application of Wavelet Transform (WT) procedures to the images, utilizing specific algorithms, enhances the understanding of surface characteristics. This integrated approach contributes to a holistic analysis of the workpiece's surface roughness, combining the strengths of both signal and image processing.

The combination of FFT and WT techniques provides a detailed exploration of frequency variations and amplitudes across different surfaces. This analysis offers a comprehensive perspective on the workpiece's surface quality, emphasizing the importance of integrating multiple techniques for a thorough understanding of surface roughness in machining processes.

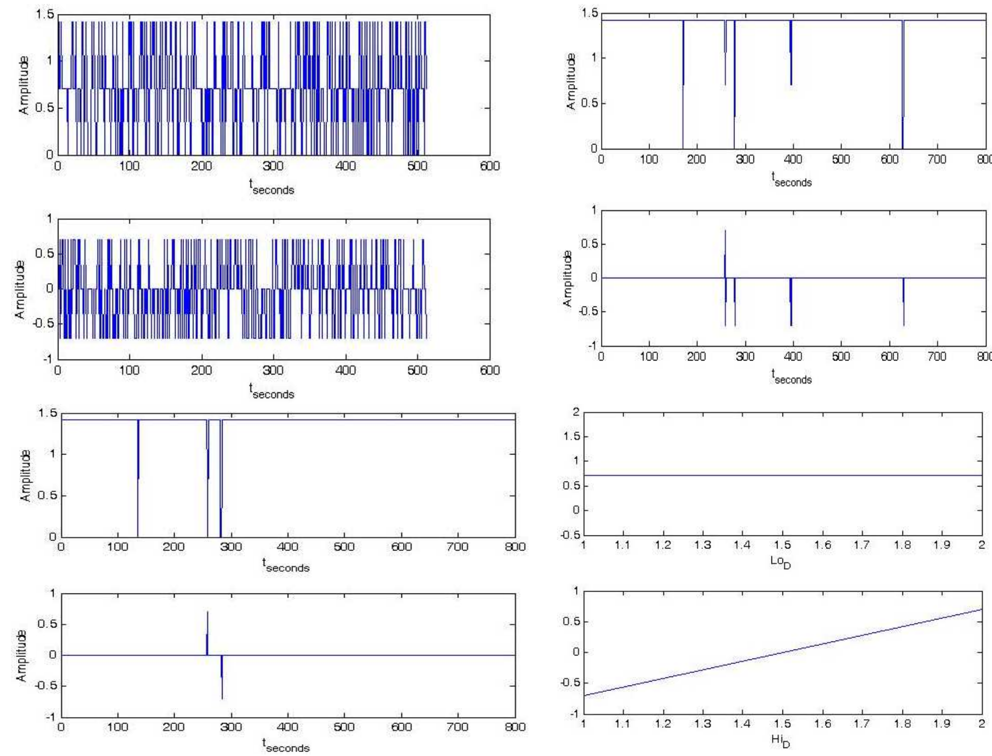

Fig. 9. The signals of smooth (upper left), medium (upper right), coarse (lower left) surfaces and low and high-pass filters (lower right) after WT analyses with haar method

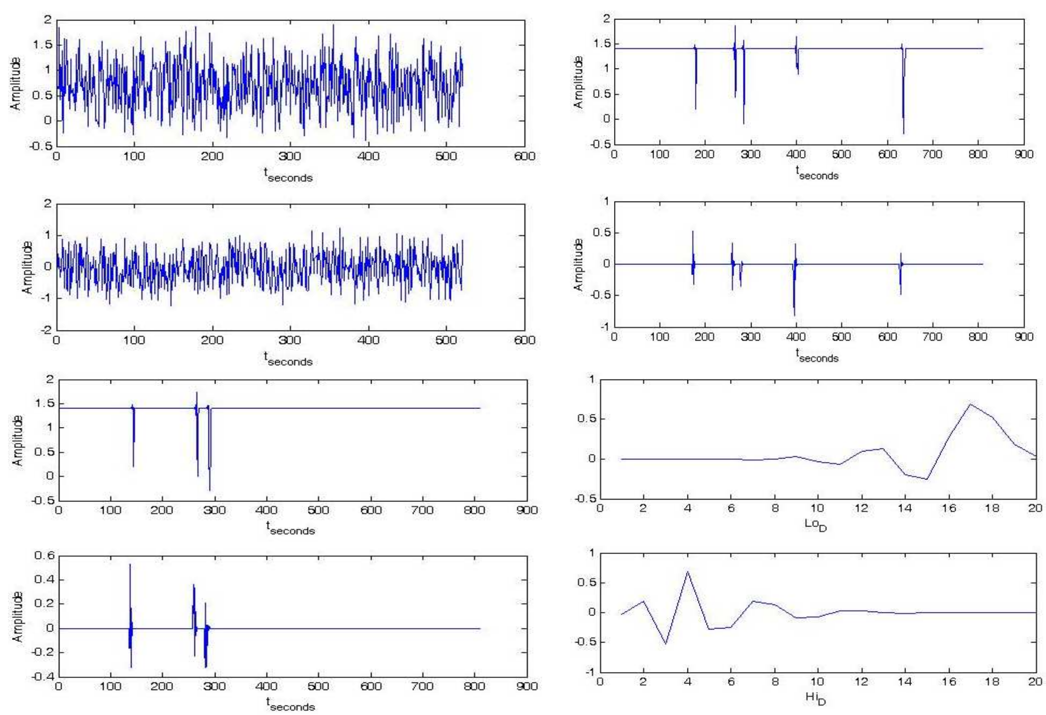

Figure 10. The signals of smooth (upper left), medium (upper right), coarse (lower left) surfaces and low and high-pass filters (lower right) after WT analyses with db10 (Daubechies filter order 10) method

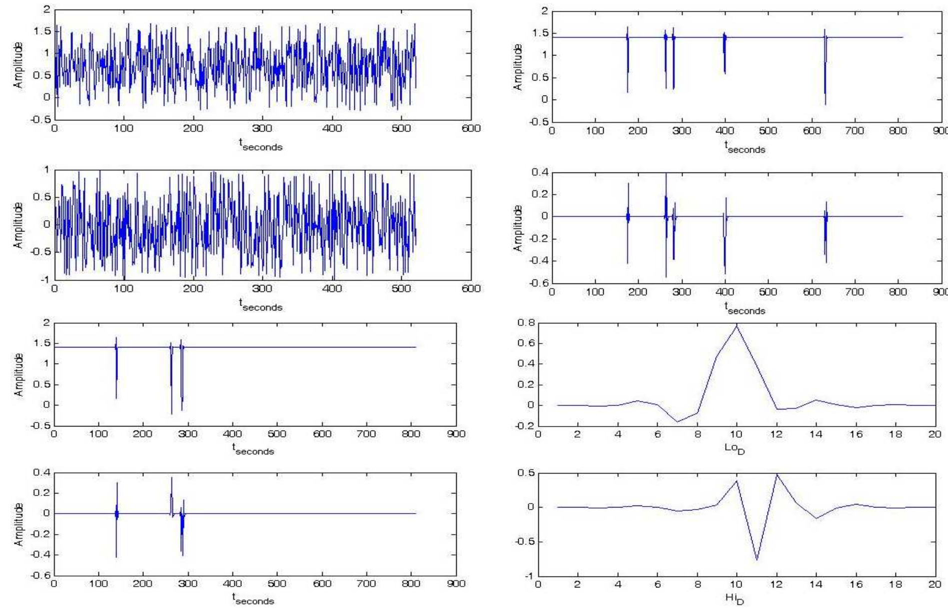

Figure 11. The signals of smooth (upper left), medium (upper right), coarse (lower left) surfaces and low and high-pass filters (lower right) after WT analyses with sym10 method

Figure 9 offers a comprehensive examination of signals obtained from smooth, medium, and coarse surfaces through the implementation of the Haar method in WT analysis. The upper left, upper right, and lower left sections meticulously showcase signals corresponding to smooth, medium, and coarse surfaces, respectively. Meanwhile, the lower right portion presents the associated low and high-pass filters, significantly enhancing the depth of the frequency domain analysis. This visual representation provides an intricate portrayal of the signal characteristics, allowing for a detailed understanding of how the Haar method in WT analysis captures and distinguishes features across varying surface textures. In Figure 10, a similar analysis is conducted with the db10 (Daubechies filter order 10) method in WT, presenting signals and filters for each surface type. Figure 11 extends the analysis with the sym10 method (Symlets filter order 10) in WT, offering signals and filters. The integration of diverse WT methods reveals a consistent pattern: smooth surfaces exhibit higher frequencies, indicating a smoother texture, while intermediate and coarse surfaces display lower frequencies, corresponding to rougher textures. This consistent pattern highlights the efficiency of the selected WT methods in characterizing surface textures through their frequency components. These observations make a substantial contribution to comprehending subtle variations in surface roughness. Moreover, the incorporation of diverse Wavelet Transform (WT) methods not only encourages a more in-depth analysis but also facilitates an interpretation of frequency variations, providing a refined and precise evaluation of workpiece surfaces. The strategic introduction of low and high-pass filters further refines the analytical process, enabling a concentrated examination of specific frequency ranges. This targeted investigation contributes significantly to a thorough characterization of surface features, releasing subtle details in topography.

The refined approach adopted in this study goes beyond a mere surface-level examination, offering a comprehensive understanding of the intricate topographical aspects inherent in machined surfaces. By enhancing our assessment of surface roughness through the utilization of WT methods and specialized filtering techniques, this research lays the groundwork for a more detailed exploration of workpiece surfaces. In doing so, it not only enhances the current state of knowledge in surface quality assessment but also presents opportunities for improved control and optimization of machining processes in the area of manufacturing.

5. CONCLUSION

This study introduces a novel perspective on surface roughness determination, focusing on the frequency components of signals acquired from measurements. While conventional methods rely on time-series signals for surface roughness parameters, this research delves into the frequency aspects of these signals. The application of both FFT and WT emerges as a pivotal approach to reveal the roughness characteristics of surfaces. The results obtained through FFT and WT analyses offer a correlation with established 2D surface roughness parameters like Ra, Rp, Rv, Rz, Rq, etc. This innovative methodology enriches the understanding of surface texture by integrating frequency dynamics, elevating the depth and precision of surface roughness assessment beyond traditional time-series analyses.

For prospective research directions, the integration of machine learning algorithms emerges as a promising avenue to enhance the predictive accuracy of surface roughness. A forward-looking approach could involve the implementation of real-time monitoring systems during machining operations to provide dynamic insights into surface quality fluctuations. Additionally, exploring the correlation between signal-based analyses and the functional attributes of machined components could yield valuable insights, thereby optimizing not only surface roughness but overall operational performance. As technological advancements in signal processing and imaging continue to evolve, there exists considerable potential for further refinement and expansion of surface quality assessment methodologies in the field of manufacturing processes.

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Evaluarea calității suprafeței bazată pe semnal în producție

Rezumat: Această cercetare investighează evaluarea calității suprafeței în prelucrarea prin tehnici de prelucrare a semnalului, concentrându-se pe Transformata Rapidă Fourier (FFT) şi Transformata Wavelet (WT). Semnalele, extrase din imagini de microscop confocal prin utilizarea instrumentelor de prelucrare a semnalului ale Matlab. Această cercetare a explorat eficacitatea FFT și WT în evaluarea rugozității suprafeței, utilizând suprafețe aspre, medii și fine ca materiale de probă. Semnalele de rugozitate de pe aceste suprafețe au fost supuse prelucrării FFT și WT, dezvăluind fezabilitatea utilizării acestor tehnici pentru evaluarea rugozității suprafeței. O evaluare a performanței a comparat aceste metode pentru a determina cea mai potrivită tehnică pentru discernerea topografiei suprafeței. Concluziile îmbunătățesc înțelegerea evaluării calității suprafeței, oferind perspective valoroase pentru selectarea metodologiilor optime adaptate la aplicații specifice.

Ismail BOGREKCI, Professor, Aydin Adnan Menderes University (ADU), Mechanical Engineering Department, ibogrekci@adu.edu.tr, 09010 Aydin, Turkey.

Pınar DEMIRCIOGLU, Professor, Aydin Adnan Menderes University (ADU), Mechanical Engineering Department, pinar.demircioglu@adu.edu.tr, 09010 Aydin, Turkey; Visiting Professor, Technical University of Munich (TUM), Mechanical Engineering, pinar.demircioglu@tum.de, 85748 Garching, Germany.