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Analysis of the properties and geometric characteristics of machined parts using computer vision

Análisis de las propiedades y características geométricas de piezas maquinadas mediante visión por computadora

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Abstract

In milling contour profiles, tools create minute surface variations known as roughness. An algorithm is proposed to analyze the profile dimensional variation in milled parts by an artificial vision and Fourier descriptors as a measurement technique. The proposed method is based on the Fourier spectrum to analyze three profile signatures extracted from an image of a milled part with the aim of measuring the variation in three materials. It is found that when performing the profile machining process, the combination of the parameters: spindle speed, feed rate, cutting depth, and coolant fluid influence the dimensional variation of the part. The proposed approach concludes that this inspection method is faster and more efficient to guarantee the quality of parts manufactured by machining.

Artificial vision, Fourier descriptors, Inspection, Geometry, Milling

Resumen

En el maquinado de perfiles de contorno por fresado, las herramientas crean variaciones superficiales diminutas conocidas como rugosidad. Se propone un algoritmo para analizar la variación dimensional del perfil en piezas fresadas mediante visión artificial y descriptores de Fourier como técnica de medida. El método propuesto se basa en la obtención del espectro de Fourier para analizar las firmas de perfil extraídas de una imagen de una pieza fresada con el objetivo de medir la variación en tres materiales. Los resultados determinaron que, al realizar el proceso de mecanizado del perfil, la combinación de los parámetros: velocidad del husillo, velocidad de avance, profundidad de corte y fluido refrigerante influyen en la variación dimensional de la pieza. El enfoque propuesto contribuye a la implementación de un nuevo método de inspección más rápido y eficiente para medir la rugosidad de piezas fabricadas por mecanizado

Visión artificial, Descriptores de Fourier, Inspección, Geometría, Maquinado

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1. Introduction

Inspection of precision parts manufactured by computer numerical control (CNC) is a fundamental process to determine the quality of manufactured products and meet customer requirements (Meraz M. & Reynoso J., 2022). Today, the aerospace and automotive industries require the manufacture of increasingly precise components. It is necessary to inspect the geometric and dimensional characteristics of machined products for quality control. In the machining process, it is not feasible to perform a complete inspection on all manufactured products. The use of sampling techniques generates costs for companies (Prabhakar et al., 2020). Machined parts must meet a certain quality, specific surface roughness and profile accuracy. To measure these characteristics it is necessary to evaluate their geometric and dimensional tolerances because cutting tools leave marks on the contour and surface of the machined part (Seeman et al., 2010). It depends on the cutting conditions and parameters that these marks are not so noticeable.

Nowadays, machine vision (VA) systems are widely applied to perform operations that humans can hardly perform, such as object recognition, flaw detection or quality control. VAs use image processing and machine learning algorithms for image classification, object detection, object tracking, and image segmentation using deep learning techniques and convolutional neural networks.

Image processing is a physical process of converting an image signal (Russ & Russ, 2017) into data to be processed and analyzed, in order to modify the image view, add dimensionality to image data, work with masks and calculate statistics, distort images, specify regions of interest, manipulate images in multiple domains, enhance contrast, and filter, extract, and classify (C. Wang et al., 2020). The use of image processing can help produce new creations, recognize an object just by its image processing silhouette (Leon et al., 2000), and save time and cost (Tiagrajah & Razeen, 2011). Some 2-D recognition methods have relied on Fourier invariant moments and descriptors to describe silhouettes. Fourier descriptors (DF) have been applied to recognize 2-D objects with close shape boundaries (Isaza et al., 2020) and for image retrieval (Zhang & Lu, 2003).

It has been applied in automatic dimensional inspection of machine part cross sections (J. Wang et al., 2019) and implemented in 2-D partial shape classification (Fang et al., 2020).

In this correspondence, we present a method for dimensional variation inspection of milling parts using DF. The method estimates the DF corresponding to the full closed limit curve using a computer vision algorithm to analyze a 2-D image in the space domain given by transforms in the frequency domain.

2. Development

The main problem is that the measurement of roughness is a laborious process that requires specialized equipment and that it is not feasible to perform it on all machined parts. Starting from the fact that roughness can be represented as a continuous signal in space called signature, and that every signal is formed by a sum of sines and its analysis is more complex.

The analysis of the roughness in the frequency domain using the Fourier transform is proposed as a faster and easier method to analyze a two-dimensional signal. The analysis will be performed with the use of Fourier descriptors (DF) to generate the spectrum of each test and to determine which signature presents more frequency and in which material, with this the conditions that generate the roughness in the machining will be determined. The experimental method is based on the analysis of the dimensional variation produced by the contour milling process in three types of materials through a computational algorithm that transforms the spatial domain of the 2-D image f(s) in the frequency domain F(u) using Fourier descriptors called VA-DF.

The project arises since most of the theoretical and experimental studies on the machining process are based on the measurement of shear forces and stress (Soori & Asmael, 2022) and only focus on surface roughness analysis with the application of computer vision systems.

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3. Methodology

The following describes the materials and methods to be employed in this research project to perform the analysis tests of the geometrical properties of CNC machined parts by DF through a VA algorithm.

3.1. Materials

For the design of the VA-DF algorithm and the performance of functionality tests, computer equipment and software with the minimum specifications for its correct performance shown in Table 1 were used.

Equipment Features	Required software and licenses
11th Generation Intel®Core™i7 processor.	Python
5.0GHz speed.	Minitab/ SPSS
Memory 8-16GB RAM.	Matlab-Simulink 2021
Free disk capacity 512GB SSD.	Visual studio
Windows 11 Operating System	SolidWorks CAD/CAM 2021

Table 1 Computer equipment

For the machining of the samples to be analyzed, a vertical CNC machining center from the laboratories of the Technological University of Chihuahua was used, with the characteristics described in Table 2.

Haas VF1 vertical machining center
3 axes X, Y, Z
Fanuc control, ISO codes
Table 650x356x300 mm
Spindle 8100 RPM, 30 HP
Carousel 20 tools

Table 2 CNC machine characteristics

3.2. Methods

Figure 1 shows the proposed methodology to obtain the Fourier spectrum and compares the results against a previously established reference standard.

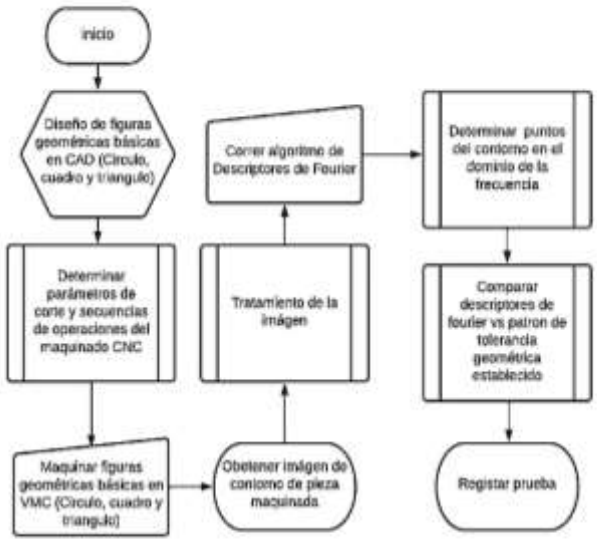

Figure 1 Methodology

3.2.1 Design

The design of the parts is carried out taking as reference a rectangular geometry of size 75 x 75 x 12 mm within a dimensional tolerance of ± 0.5 mm. The characteristics of the signatures are: curve (SG1) is a quarter circle with a radius of 20 mm, horizontal line (SG2) with a length of 25 mm and slope (SG3) of 12.5 mm length at 33.69°. Figure 2 shows the design of the test piece.

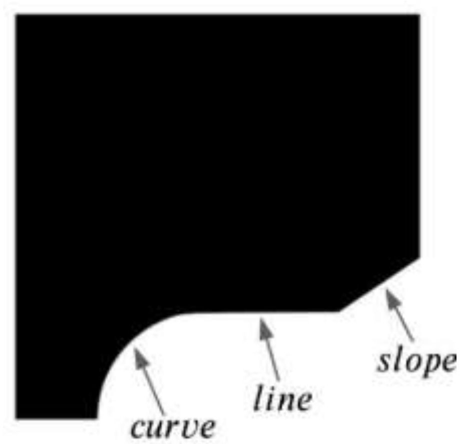

Figure 2 Test piece

The tests are performed with three different materials and their respective shear parameters described in Table 3

Materials	Vc (m/min)	Fz (mm/Flute)
Aluminum 1060	61/70	0.5/0.7
Nylacero	90/100	0.7/0.9
Plastic Delrin	27/30	0.3/0.1

Table 3 Materials and shear parameters

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The parameters were obtained from the manufacturer's data taking into account the type of cutting tool and its operation in the machining process in order to evaluate the effect of the dimensional variation produced by the profile contour milling process and then compared with the *Ground Truth (GT)* reference signal of each firm shown in Figure 3.

Figure 3 Ground Truth GT1, GT2 and GT3

3.2.2. Machining of parts

The machining program is generated based on the following sequence of operations:

1. Planing cycle (1 mm depth of cut).
2. Contour roughing cycle (2 mm depth of cut) and 3.
3. Contour finishing cycle (13 mm depth of cut, in contact with the tool face).

Once the program sequence is defined, the spindle speed and feed rate are adapted for each material, then the program is simulated and verified to analyze the trajectories in order to detect collisions or anomalies in the process, finally, the G&M code program is generated on the Haas FANUC control for VMC Figure 4.

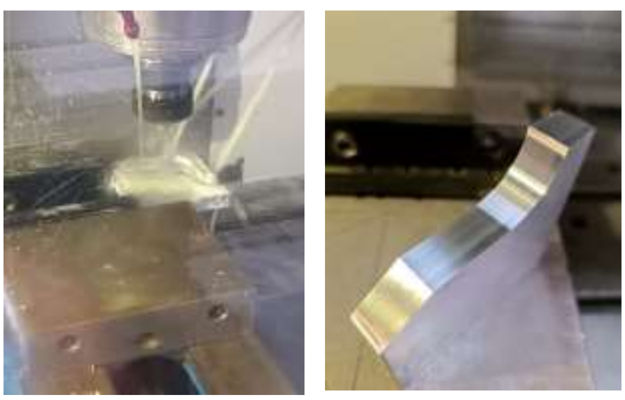

Figure 4 Machining of parts in Haas machining center

3.2.3. Generation of signatures

For the generation of signatures, first we have to capture the image of the part to be analyzed (Figure 5) with our image acquisition system since this is the input signal for the DF-VA algorithm.

Figure 5 Images captured by the acquisition system for signatures SG1, SG2 and SG3

As a next step, the signal will be subjected to a pre-processing to clean it and generate its contour through the *regionprops* function (Figure 6, 7 and 8).

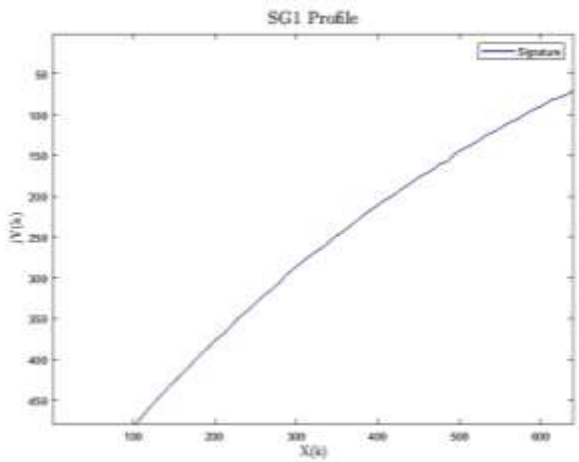

Figure 6 Contour profile for signature SG1.1

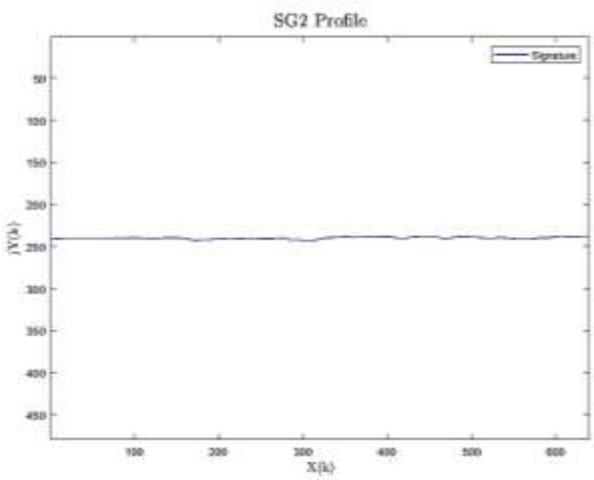

Figure 7 Contour profile for signature SG2.

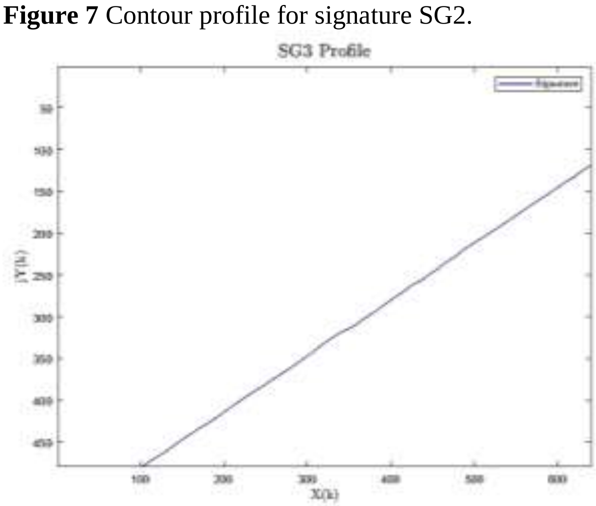

Figure 8. Contour profile for signature SG3

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When the contour of the signature is already generated, the VA-DF algorithm generates a vector of 300 elements *([r(no),.....r(n-1)]* by means of the tracking function, giving a reasonable approximation with a minimum set of points on the perimeter, obtaining a compact representation compared to the large number of points that compose the original silhouette (Jasinevicius et al., 2021). This is achieved by minimizing the objective function f(n) using the algorithm that allows making good discriminations without using too much computational power or large databases.

3.2.4. DF-VA Algorithm

To process the image, the algorithm shown in Figure 9 needs the image capture as input signal to transform the 2-D continuous signal *f(s)* into a Fourier spectrum in the frequency domain F(u). The Fourier spectrum of the geometric feature will be generated as output and compared with its corresponding WG to determine the geometric variation value of the part.

Figure 9 DF-VA Algorithm

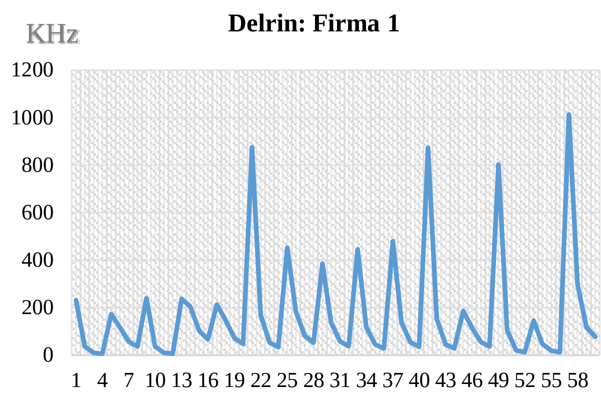
Results

Table 4 shows the results of the average Fourier spectrum (Hz) for GT1 (ξ) and its mean variation of the average Fourier spectrum (δ).

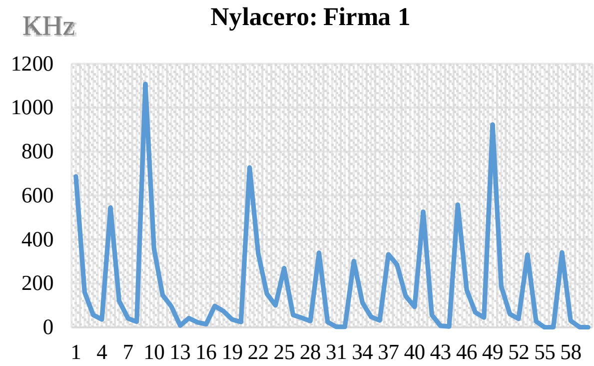
Material	Average roughness (Hz)
Black Delrin	167.9168831
Nylacero white	175.0868661
Aluminum	147.0559941

Table 4 SG1 roughness profile results

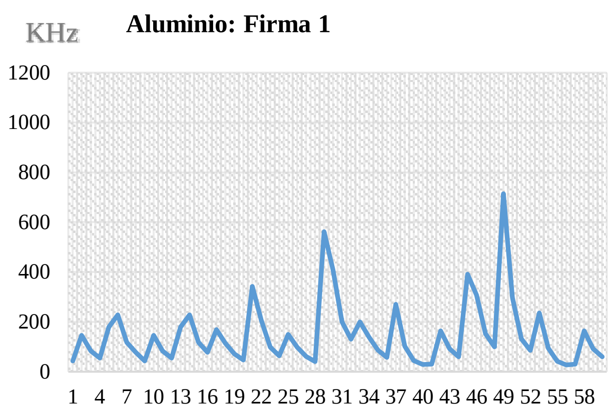
Graphs 1, 2 and 3 show the behavior of the profile as a function of frequency for the SG1 signature. In this analysis Nylon causes higher variations (*rms = 0.0039 KHz*), Delrin presents a low roughness profile (*rms = 0.0022 KHz*) and in aluminum the variation is lower (*rms = 0.0015 KHz*).



Graph 1 SG1 Delrin signature behavior



Graph 2 SG1 Nylon signature behavior



Graph 3 SG1 Aluminum Signature Behavior

Table 5 shows the results of the average Fourier spectrum (Hz) for GT2 (ξ) and the average variation of the average Fourier spectrum (δ).

Material	Average roughness (Hz)
Black Delrin	140.462
Nylacero white	194.367
Aluminum	98.36724

Table 5 SG2 roughness profile results

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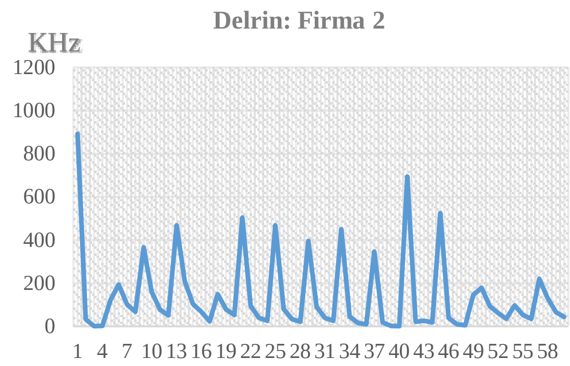
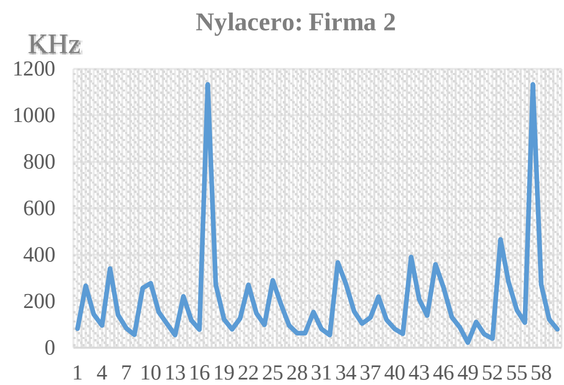
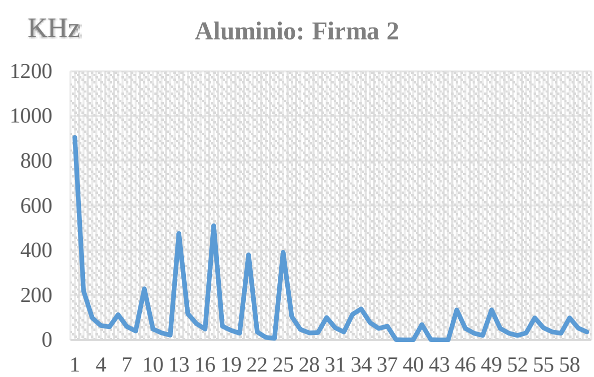
Graphs 4, 5 and 6 show the behavior of the roughness profile variation for SG2. In this analysis, we found that the dimensional variation was higher for Nylon (rms = 0.0037 KHz), lower for Delrin (rms = 0.0021 KHz) and low for aluminum (rms = 0.0007 KHz).



Graph 4 SG2 Delrin signature behavior



Graph 5 SG2 Nylacero signature behavior



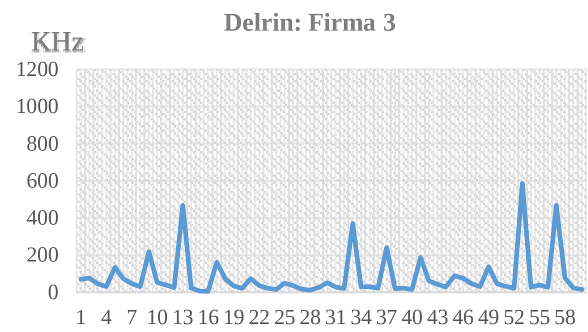
Graph 6 SG2 Aluminum Signature Behavior

Table 6 shows the results of the average Fourier spectrum (Hz) for GT3 (ξ) and the average variation of the average Fourier spectrum (δ) determined by the difference CGT3 - CGC3 in KHz.

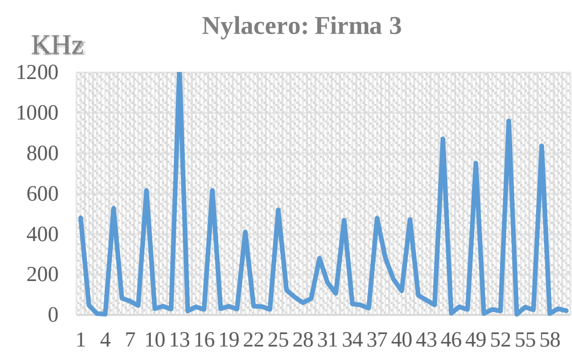
Material	Average roughness (Hz)
Black Delrin	80.40315841
Nylacero white	199.8213097
Aluminum	76.79069078

Table 6 SG3 roughness profile results

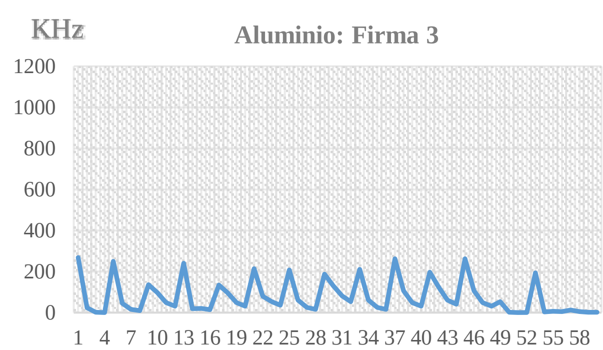
Graphs 7, 8 and 9 show the behavior of the roughness profile variation for SG3. In the analysis, we found that the dimensional variation remains higher for Nylon (rms= 0.0037 KHz), lower for Delrin (rms= 0.0019 KHz), and minimum for aluminum (rms= 0.0015 KHz).



Graph 7 SG3 Delrin signature behavior



Graph 8 Behavior of SG3 Nylacero signature



Graph 9 SG3 Aluminum Signature Behavior

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Discussion

Three signatures SG1, SG2 and SG3 were compared in terms of frequency defining the roughness profile quality, each signature was machined with its own machining parameters and the same strategy tool paths.

In the results, the analyses of the signatures show that the aluminum material presents the lowest average roughness in SG1, SG2 and SG3 due to the physico-mechanical properties of the material. It was determined that aluminum presented better machinability with respect to Delrin and Nylacero. It was also determined that the roughness depends on the machining operation in each signature, resulting in a better finish in the horizontal line due to linear interpolation than in the circular signature because the machine interpolates in two axes, and this causes a little more surface chip breakage.

Milling forces were also found to be the main factors governing dimensional accuracy, profile quality, machine vibration, spindle power requirements, power consumption and cutter life. These forces that occurred during machining were determined to produce bending, breakage or other distortions of the machined part due to the tool cutting forces acting on the part (Soori & Asmael, 2022).

With this experimental project, it is determined that in general, these distortions are generated by several factors such as depth of cut, spindle speed, feed rate, vibration and type of operation. The microscopic morphology of the free machining contour cannot be measured accurately, but an approximation would be obtained using the frequency spectrum.

Conclusions

It is determined that proper selection of the cutter path strategy is crucial to achieve the desired roughness of the machined profile in combination with the proper cutting parameters for each material. Therefore, the roughness profile measurements determine the effects of the milling profile signatures on the three materials.

In conclusion, the project addresses a crucial challenge in the characterization and understanding of rough surfaces in various industrial and scientific fields. The surface roughness of mechanical parts and materials can have a significant impact on their performance, durability and efficiency, which makes the ability to analyze and quantify this characteristic of great importance.

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