COBEM 2021 26th International Congress of Mechanical Engineering
ABCM Associação Brasileira de Engenharia e Ciências Mecânicas
November 22-26, 2021, Virtual Congress, Brazil

COB-2021-1756
DIGITAL PROCESSING AND STATISTICAL ANALYSIS OF AUDIO SIGNALS MEASURED THROUGH SMARTPHONE DEVICES FOR THE APPLICATION IN TOOL WEAR MONITORING

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Abstract. *Machining process monitoring techniques became a way to improve manufacturing systems, many methods have been studied with this intention, since the industrial revolutions. Therefore, this paper proposes to testing a low-cost wear monitoring system as a means of reduce costs of the machining process, the system is composed of a simple smartphone device used to capture audible signals emitted during the metal cutting process. The process of turning a part has been recorded through a smartphone audio recording app, in addition, microscopy images of the cutting tool were obtained before and between the process passes. This experiment was computationally analyzed using a software for RMS and DFTs calculation from techniques of signal processing. Sensors, that are currently used in the manufacturing environment, are expensive and, as smartphones are becoming increasingly popular, they can be sensors more economically viable than them. These devices gained visibility for the optimization of machining monitoring techniques revealing an interesting potential for this purpose. Although with some restrictions on the sensitivity of microphone, the smartphones can detect wear, besides optimize the incurred cost and, therefore, to be a more economically option. In the conclusions, advantages and disadvantages of the proposed methodology are presented.*

Keywords: *signal processing, machining, turning, tool life, mobile devices.*

1. INTRODUCTION

Methods for production improvements are becoming necessary in order to make faster and more efficient industrial processes with a better cost benefit. This also happens in the turning machining processes, once the monitoring techniques have been improved, it is possible to discover how the cutting tool is affected by wear and predict when a failure will occur. There is no way to avoid wear, but, with the machining process monitoring, material loss and machine downtime can be avoided or, at least, reduced. The optimization of a machining process is often related to maximizing tool life and tool wear monitoring can be critical to assist in this optimization (GAJATE *et al.*, 2010).

According to Dimla (2000), there are four predominant types of tool wear: the nose wear that results in negative rake angle that increases with time; the flank wear that wear comes from the contact between two surfaces, generating a deterioration of surface quality; the notch wear that can cause a tool failure and this is accelerated by oxidation; and the cratering, that is formed by high cutting temperatures and high shear stresses. The wears occur during the material removal process and can be classified into adhesive wear, abrasive wear, diffusion wear and fracture wear. They are an unavoidable phenomenon in metal cutting, being a source of major economic loss due machine down time and material loss (SIDDHPURA; PAUROBALLY, 2013).

Aiming to avoid the aforementioned losses, there are several studies on tool wear monitoring. Kopac and Sali (2001) developed a tool wear prediction model for monitoring the tool during a machining process according to different cutting speeds and feed rates. The study analyzed sound pressure during turning, being measured by a microphone. The signal was analyzed in the frequency domain, this showed that the increase in tool wear correlates with the increase in the amplitude of the sound wave.

In a similar research, Frigieri *et al.* (2017) investigated the relationship between audible sound emitted by turning and the machining parameters. As a result, it was observed that, extracting the main components of the power spectra, the corresponding acoustic signals have been detected and processed in the frequency domain, proving that the sound signal emitted by the machine during turning can be used to design a system that reveals the machining conditions.

In order to lower the cost of monitoring machining processes, since the processes are usually monitored by expensive sensors and hardware systems, some researchers have been studying the possibility of replacing such sensors with more affordable sensors.

Morgenthal and Höpfner (2012), claim that smartphones have significant computational power and this gives them resources for applications in the field of monitoring. In their article, they studied the use of a smartphone to monitor transient displacements using its sensors, such as an accelerometer, microphone and speakers. Studying the accuracy of measurements, the authors described as an advantage, the practicality of the mobile device, and as a limitation, the resolution of the signal that is not as defined as those of the traditional sensors used. Therefore, different areas were identified for possible applications of a smartphone as a monitoring tool.

Other authors who analyzed these applications were Matarazzo *et al.* (2018), they used the accelerometer of a smartphone to monitor the vibration of bridges, from the device's sensors, it is possible to obtain consistent information about the modal frequencies of the bridge. They concluded that the use of this instrument generates a lot of data that, in a long period, can contribute to reducing the maintenance cost, in addition to making assumptions about the flow of people passing by, which can increase the life expectancy of the bridge.

Due to the popularization of smartphones and other mobile devices, it could be interesting to explore its functions and discover its viability in industrial processes, so that these can be done with a lower built-in cost. Thus, the purpose of this work is to verify the applicability of tool wear monitoring in a turning through sound signals captured by a microphone of a common smartphone, aiming to facilitate the monitoring of machining processes, reducing its cost through new methodologies.

2. METHODOLOGY

In this work, an experimental research was carried out with the proposal to validate the possibility of reducing costs of the machining process by testing a low-cost wear monitoring system composed of a simple smartphone device used to capture audible signals emitted during the metal cutting process and the data obtained were analyzed computationally.

2.1 Experimental test

The experiment was carried out with a universal lathe machine Imor prn-320 with 1.8 kW power output, maximum speed at 1500 RPM, average cutting speed was kept at 100 m/min, feed was set as 0.047 mm and depth of cut was set as 1.0 mm, all these parameters were chosen based on both machine limitations and tool maker suggestions, besides dry cutting was employed. In this machine was used a tool holder PDJNR 2020 K12 with a DNMG 150404-PF insert, class GC4325 (ISO HC P25). Such insert was specially applied for processing steel at high temperatures. The authors recorded sound signals in the audible range with the smartphone microphone, using an audio record application. The generated file was sampled with a frequency of 44.1 kHz in mono mode and it was computationally analyzed for verification of the applicability of mobile devices to monitor cutting tool wear.

The machined part was cylindrical, 150 mm length and 65 mm diameter with hot work tool steel grade VEX (alloyed with chromium, molybdenum, vanadium and aluminum), special purposed for manufacturing of dies for extrusion of non-ferrous alloys (VILLARES METALS, 2013) as-annealed, with 230 HB. In this piece, four passes were made with the tool described above, these passes occurred until the wear on the insert was prominent. In the Figure 1, it is possible to see an illustration of the setup in which the experiment took place.

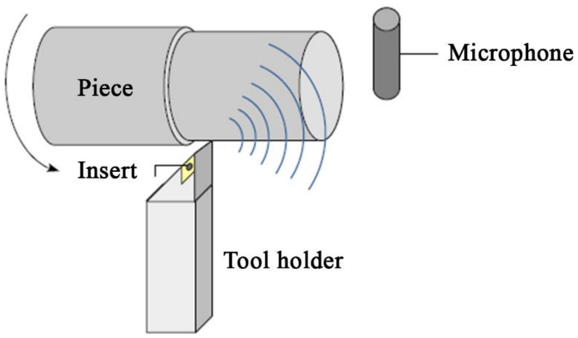

Figure 1. Experimental setup of tests for wear monitoring.

Images of the worn were captured with a stereo microscope Nova XTD 30, with 40 times magnification equipped with a CCD camera, to serve as a reference for the tool wear state and for verification of visible wear levels on the flank and exit surface of the cutting tool. The insert was analyzed before the start of the cutting process and between the process passes. This ensured the possibility of checking whether the wear was visible when the sound signal changed.

In each pass, an audio file was recorded as shown in the Figure 2.

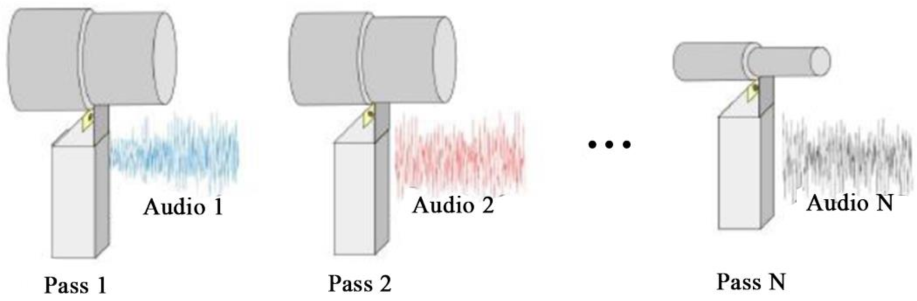

Figure 2. Summary of the experimental methodology for wear monitoring.

During the experimental tests, it was possible to perform 4 complete cutting steps, while the fifth one had to be interrupted due to the tool failure, each one of these completed steps represents an analyzed audio file. The first two steps were done using a spindle rotation of 600 RPM, while the remaining ones had a rotation of 475 RPM. This variation had to be applied in order to maintain an average cutting speed of 100 m/min. Table 1 summarizes the experimental tests.

Table 1. Summary of experimental tests

Cutting Step	Rotation [RPM]	Description
Step 1	600	Completed
Step 2	600	Completed
Step 3	475	Completed
Step 4	475	Completed
Step 5	475	Interrupted (due to tool failure)

After the completion of the experimental part, the data obtained were analyzed computationally with the aid of the MATLAB numerical analysis software.

2.2 Method used for data analysis and processing

The audio files obtained in the tool wear process were analyzed from the root mean square (RMS) values calculated from the time-domain signals and in the frequency domain using the discrete Fourier transform (DFT). The estimated probability density function, representing the statistical distribution, was also observed.

The RMS is a measure of signal energy that can be calculated by:

$$RMS = \sqrt{\frac{1}{N} \cdot \sum_{j=0}^{N-1} \left(x_j^2\right)} \tag{1}$$

where N is the number of points in a signal that can be obtained as a function of time and x is the captured signal. For each audio file obtained, a RMS calculation was performed, in addition, each audio, referring to the passes, was subdivided into ten parts and for each part this calculation was also performed. In this way, it was possible to draw boxplots for a more complete analysis of the statistical behavior of the signal features.

For this second part of the analysis, data from the beginning and the end of the turning process in each audio were excluded, eliminating machine downtime. In order to assist in the calculations, the MATLAB software, which has functions for calculating the RMS, was used.

In this work, the histogram was also used which is a graphical representation of a frequency distribution of a random variable. The horizontal axis represents a class, in this case, the distribution of the sound signals and on the vertical axis it is possible to see the frequency of the analyzed sampling.

Another analysis was carried out using boxplots of the RMS and frequency data and it was calculated the signal’s probability density function (PDF), this function shows what the probability is that a random variable falls into a particular range and this can be calculated by the area formed under the density function, the MATLAB software, used in this research, has a function that provides these results graphically.

The function used in MATLAB was the “ksdensity”, that computes one or two dimensional kernel density or distribution estimate, that is a non-parametric probability density function. The tool transforms the obtained data using a log function and estimates the density of these values, after this, it transforms them back to the original scale, when it’s not possible to estimate about a random variable, this toll is used (HILL, 1985).

The last analysis made on the files was based on the DFT of the audio signal, the Equation 2 describes this calculation (SHIN; HAMMOND, 2008), with the purpose to identify dominant frequencies and correlate them with characteristic values of the cutting process.

$$X_k = \sum_{n=0}^{N-1} \left(\mathrm{x}_n \, . \, e^{-j \, . \frac{2\pi}{N} . \, n \, . \, k} \right) \tag{2}$$

where X_k is the signal transformed to the frequency domain and N is the number of samples of the signal. Also, with the subdivided audios, it was possible to make a more detailed analysis by statistical methods with the main peak frequencies and the area below the graph computationally obtained.

The analyzes of this research allowed a more complete conclusion regarding the applicability of smartphone microphones instead of the usual sensors for monitoring tool wear what can make the process feasible.

3. RESULTS

The sound signals, obtained through the turning experiments, were analyzed with the aid of MATLAB software, with the analysis being divided into the time domain and the frequency domain, and are explained below.

3.1 Results in the time domain

First, four tool passes were made in the turning, generating an audio file for each pass, recorded with a smartphone microphone. This amount was sufficient for being possible to notice a variation in the audible sound signal. These files were read in the software and each of them generated a graph in the time domain, as seen in Figure 3.

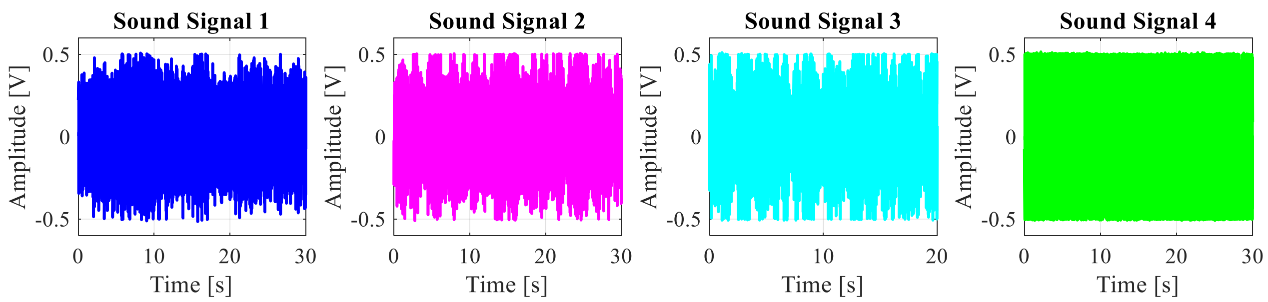

Figure 3. Sound signals in the time domain.

It is possible to perceive that the sound amplitude is altered along the process according to what is shown in the graphical analysis. The graph of the first sound signal has a lower amplitude variation, on the other hand, the graph of the last sound signal has a high amplitude variation, which can be caused by the occurrence of a tool wear process throughout the machining process. This fact can be confirmed when comparing the graphs with the images obtained, as it will be possible to see in the section 3.3 of this work, since in the fourth pass, the tool showed aggravated wear.

In the graphs in the Figure 3, it is possible to see the limitation of the smartphone microphone, from the second sound signal, it is clear that the audio file starts to saturate. Since the recorder does not demonstrate amplitudes higher than 0.5 V, the device may not be able to properly sample strong sound signals. Because of this apparent saturation, the authors made a sound signal histogram to understand how the signal would be distributed in the amplitudes between -0.5V and 0.5V and it was possible to observe that, despite the saturation, the distribution varies as the tool wears out as seen in Figure 4.

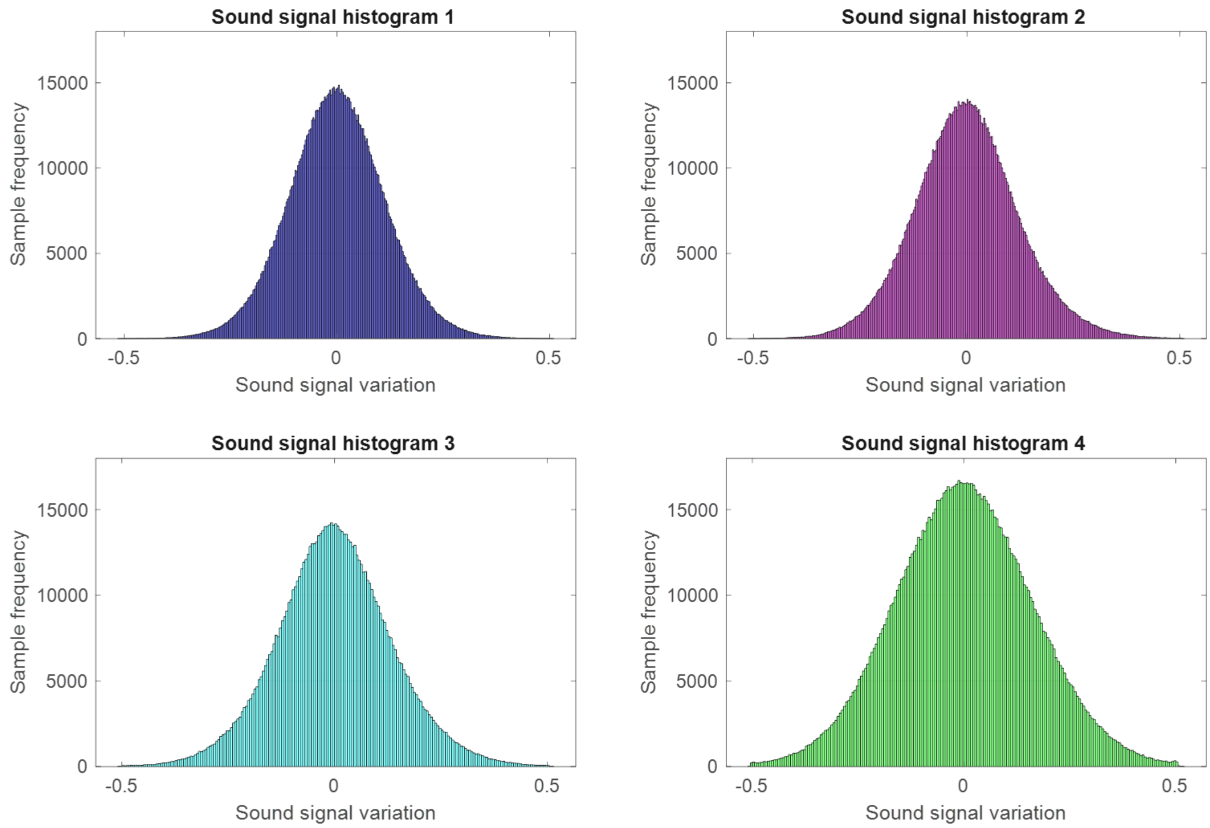

Figure 4. Sound signals histograms comparison.

It can be noted, therefore, in the graphs of Figure 4 that in the analyzed interval there are consistent differences between the signal distribution when the tool is in optimal conditions of use, as seen in histogram 1, and when its wear starts to increase, as in histogram 4. Another way to analyze this distribution is through a graph of a probability density function, thus the PDF was plotted in the MATLAB software, as seen in Figure 5.

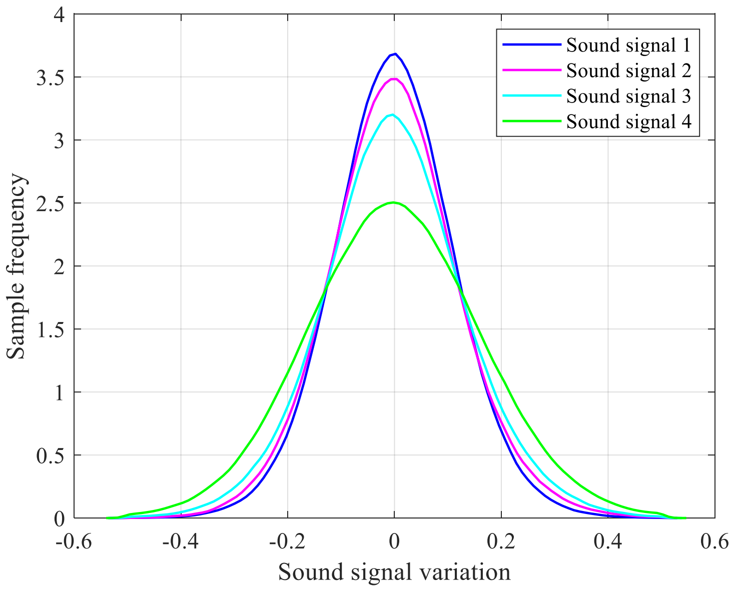

Figure 5. Sound signals probability density function comparison.

The curves in this graph are smoothed, therefore, the saturation may not be evident, although, despite of this, it is possible to see the difference between distributions of each curve. Since the area of each plotted graph must correspond to one, when plotting the graphics, referring to the four sound signals, overlapping, the greater the amplitude of the distribution, the flatter the curve and vice versa.

The first sound signal has the smallest amplitude distribution among the four analyzed audio files, which means that most of your variables have zero amplitude and this curve is the narrowest. As the turning process progresses, the sound signals gain more dispersion, the curves become wider, as the amplitudes do not remain mainly at zero.

In order to demonstrate the difference between signals, the calculation of the RMS was carried out over the turning process. First, the RMS was calculated for each audio file, representing each pass, and then the RMS was calculated for each of the ten subdivisions of the four audio files. The values obtained, in the subdivisions of the files, maintained a correspondence with the general RMS of each pass. With these RMS data and understanding the dispersion that occurred in the machining process, a boxplot of these values was plotted to understand their variation over the passes, as shown in the Figure 6.

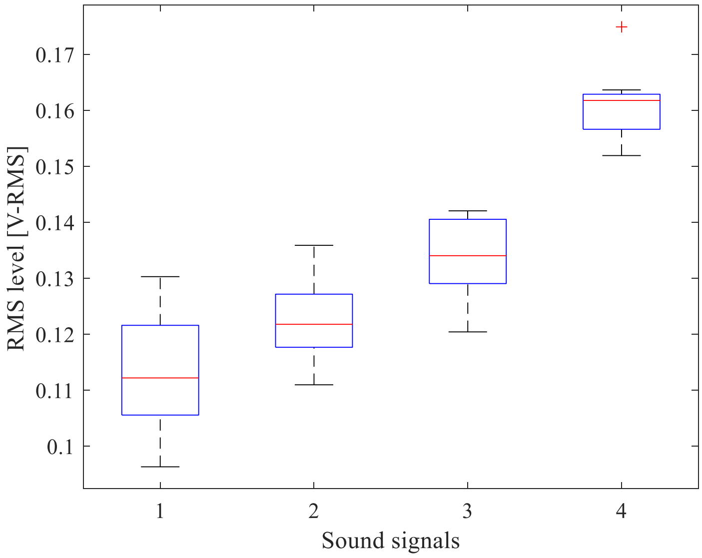

Figure 6. Sound signal RMS boxplot.

The graph in the Figure 6 reinforces the information obtained by the graphs in the Figure 3, the RMS of the first three passes remained similar, while the RMS of the fourth pass has higher values. The greater the dispersion of a signal, the greater its standard deviation, this relationship can be exemplified from the RMS boxplot, since increasing the standard deviation also means increasing the value of the RMS.

3.2 Results in the frequency domain

Continuing with the research, the audio files were analyzed in the frequency domain. Using the DFT on both entire audio files and their subdivisions, it was possible to perform an analysis similar to RMS. The DFT was used to transform each of the ten subdivisions of each audio file to the frequency-domain. These ten DFTs were averaged to suppress effects of uncorrelated noise. The averaged DFTs of the four audio signals are illustrated in Figure 7.

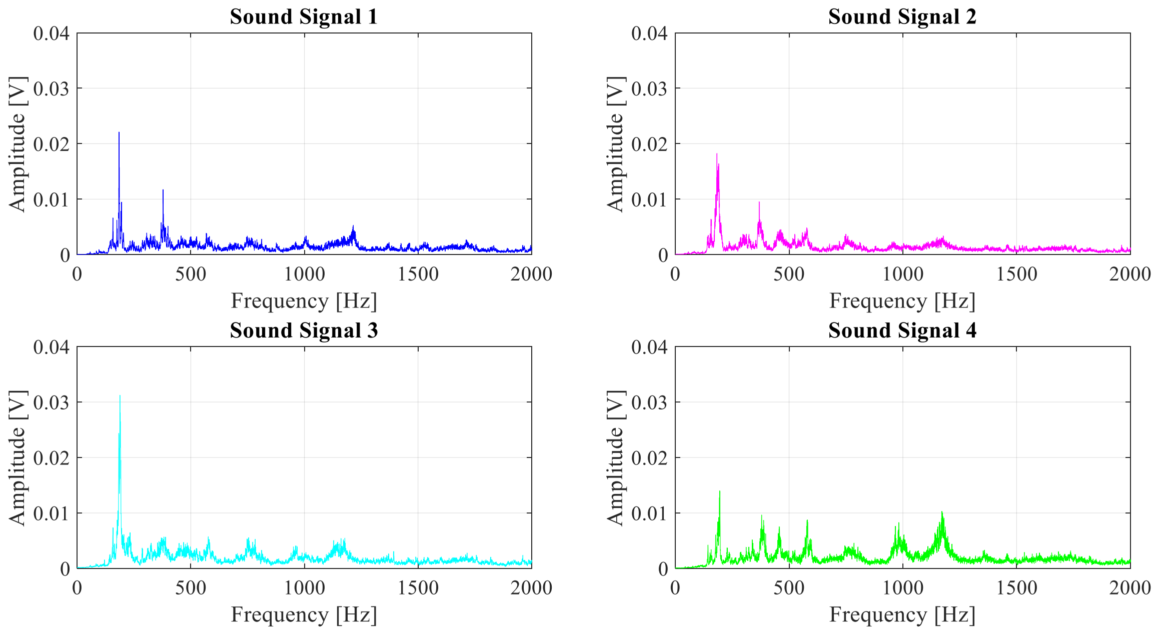

Figure 7. Sound signals average frequencies.

Through the analysis of the averages of frequencies in each audio file, it is possible to notice that the highest frequency peaks are between 180 and 200 Hz, this is due to the sound of the turning and also to external sounds that may have been captured by the microphone. The next peak frequency is at about 400 Hz, which could be the lathe motor's effect.

As in the case of sound signals, the fourth audio file in the frequency domain also presents variations in relation to the first three, in the boxplot of the frequencies, it is possible to better visualize these variations, as seen in the Figure 8.

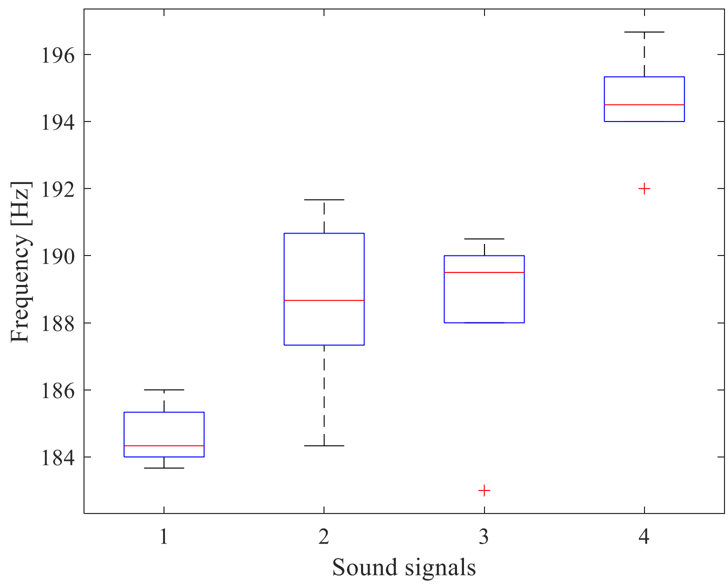

Figure 8. Sound signals frequencies boxplot.

The first three files have a similar frequency range, the fourth audio has a higher peak frequency, this can be explained by the sharp wear shown by the tool in recording this audio file. As, in addition to the peak frequency, that were around 200 Hz, there were frequency variations in other parts of the domain, like it is possible to visually perceive in the frequency graphs in Figure 7. Because of that, the areas under the frequency curve between 800 and 1400 Hz were calculated, to discover if there were differences between the four audio files at higher frequencies. The boxplot, in Figure 9 below, shows the results of this new analysis.

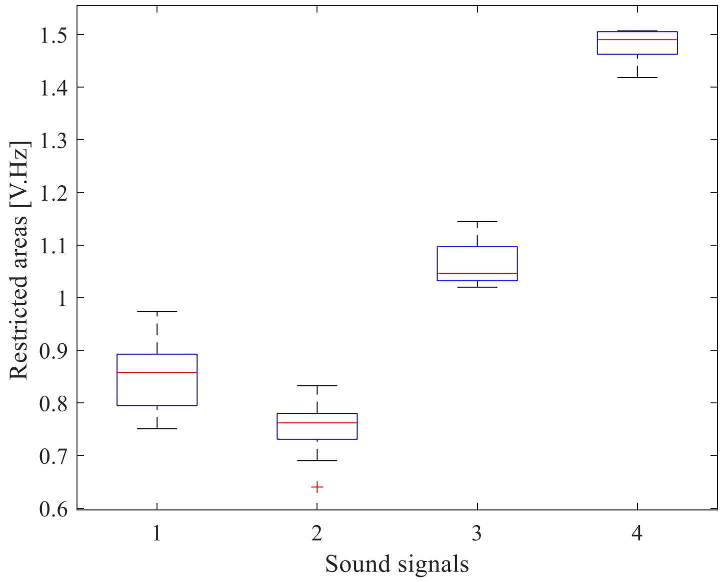

Figure 9. Restricted areas under sound signals frequency boxplot (from 800 to 1400 Hz).

When restricting the area under the frequency between 800 and 1400 Hz, it is possible to notice that, as well as in frequencies close to 200 Hz, in higher frequencies, the audio file number four also differs from the others. The last audio file features larger restricted areas, demonstrating the high wear of the tool, which reinforces the results seen in the analysis of sound signals in the time domain.

3.3 Comparison of analysis with images

For a better understanding of the data analysis from the two previous sections, this section will approach the visual analysis of cutting tool wear. The Figure 10 confirms the results obtained, showing the visual evolution of tool wear along the turning passes obtained from microscopy images.

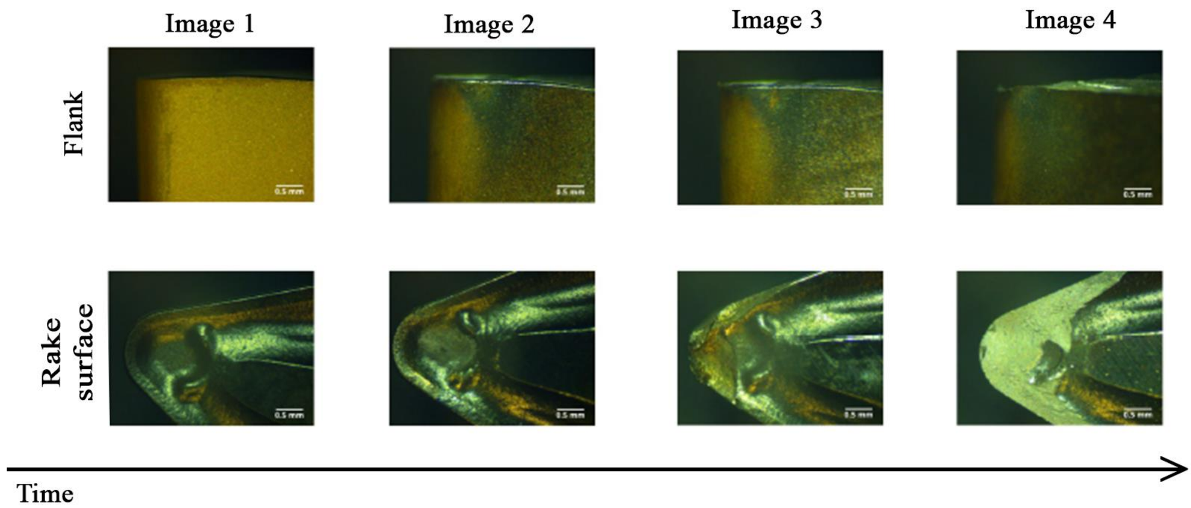

Figure 10. Visual wear of the cutting tool throughout the turning process

The Image 1 was taken before starting the machining process, the tool was still intact with no visible wear, this image serves as a reference for comparing the wear that occurred in the next passes and that could be seen in the other images. The Image 2 was obtained after the third pass of the tool, this space between images corresponds to the little variation in visible wear, as confirmed with the audios of the first three passes, there were no major structural changes up to this point.

On the other hand, the Image 3 was obtained after the fourth pass, in this case it is possible to perceive a little chance compared to the other two. The tool already has visible wear with small portions of adhered material, which also confirms the audio analysis because the sound analysis obtained from the fourth pass has changes in relation to the other passes. In the last picture, the Image 4, it is possible to see the complete wear of the cutting tool. A fifth pass attempt occurred on the machined part, which caused the tool chipping, therefore, as the Image 4 was taken after this attempt, it is possible to clearly see the prominent wear that occurred.

Thereby, the relationship between the sound signal analysis of the turning process and the microscopic images bring reliability to the studies and, consequently, to the data obtained, because they demonstrate tool wear at the same time in the process, even with saturation limiting the range to be analyzed. As the RMS and frequency data change from the fourth pass, the modifications in the microscopy images also start to appear from this pass.

4. CONCLUSIONS

Due to the analysis carried out in the time domain and in the frequency domain, with the audio files obtained through a smartphone microphone in a turning process, it was possible to test the applicability of this device for monitoring machining processes.

The reason for the saturation occurrence is likely caused by a limitation of the smartphone's hardware and software. This is clearly an important limitation of the proposed methodology regarding the proposed alternative for tool wear monitoring since sound samples with higher frequencies and amplitudes may be underestimated.

Thus, the results showed that, despite this saturation and the poor sound quality of the recording by the smartphone app, as seen in Figure 3, the microphone sensor was able to perceive relevant variations to the tool wear process, being able to detect when tool wear is prominent in your monitoring.

Matarazzo *et al.* (2018), in their study, used smartphone sensors to monitor the vibration of the bridges and they also concluded that there is applicability for smartphone sensors in engineering areas. Despite less precision in monitoring, smartphone sensors can be used to reduce costs in the monitoring process.

Smartphones are devices that are becoming more viable and popular, besides being in constant improvement of their features. Thereby, one of the advantages of using such a device is the cost-effectiveness of this type of monitoring, for example, by using it, smaller companies can reduce economic losses. There are also limitations, such as the low quality of the sound signal captured and audio saturation at higher magnitudes, however, the device is able to distinguish when the tool is worn out and when it is in good condition.

Therefore, due to the popularization of the device and the results seen in this paper, it is possible to conclude that the replacement of conventional sensors by smartphone sensors can be done, even with some limitations.

5. ACKNOWLEDGEMENTS

The first author would like to thank the ICT-SR UFSCar program for the institutional support that allowed this research to be carried. The authors are grateful to the São Paulo Research Foundation (FAPESP) through the processes nº 2015/25146-3 e 2018/25135-0 for the promotion that allowed the purchase of the computational tools used in this work. The authors are also grateful to the CNPq Universal grant (process 432002/2018-9) for partially promoting this research.

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