STUDY OF SURFACE ROUGHNESS OF GROUND CERAMICS BY VIBRATION SIGNAL ANALISYS

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Abstract. *Monitoring the grinding of ceramics using the vibration signal has been presented as an alternative for the diagnosis of the workpiece surface. This paper has the objective of studying the vibration signal through spectral analysis in order to monitor the grinding process, and looking for the best parameters that could be related to the surface roughness in the finished workpieces of ceramics. Indeed, tests were performed at three different cutting depths: 25µm, 105µm and 350 µm adopting two different feed speeds (vw), which allow for low to severe grinding conditions. A surface grinding machine with a synthetic diamond grinding wheel was employed, and the surface roughness (R_a) of each finished workpiece was measured at four points along its surface, using a portable roughness measurer. An accelerometer fixed on the workpiece holder was used and the signals were collected by an oscilloscope with a sampling rate of 2 million samples per second. Digital signal processing techniques were performed, such as Welch method to obtain the Power Spectral Density (PSD) of vibration signal. It was possible to identify frequency bands between 1 kHz and 10 kHz that best correlated to the surface roughness. It was observed that the increase of* v_w *during grinding causes the spectral density values to increase and surface roughness to decrease. There is a correlation between vibration and roughness for each speed studied. This correlation is lost when one considers both speeds simultaneously investigated for analysis. It could be then verified that the vibration can be used to monitor the grinding condition and, in turn, its consequence on the workpiece in terms of surface roughness. A real-time monitoring system, using a low-cost hardware, can be proposed, since the found frequency bands are below 10 kHz..*

Keywords: *Vibration signal, Grinding monitoring, Advanced ceramics, Surface roughness.*

1. INTRODUCTION

Interest in grinding of advanced ceramics has grown substantially with the widespread use of ceramic components in various engineering applications such as cutting tools, automobile valves, packing (sealing) elements, bearings, pistons, rotors, etc. (Hu and Chandra, 1973). The advantage of ceramics over other materials includes high hardness and strength at elevated temperatures, chemical stability, attractive high temperature wear resistance and low density (Bandyoupadhyay, 1995). However, the favorable features are accompanied by difficulties associated with machining and grinding mainly because of the high hardness and stiffness of these advanced ceramics. The grinding process, the most important step of the advanced ceramic machining process, is highly complex and involves the contact between a large numbers of abrasive particles with the surface of the workpiece. The grinding process allows a precise dimensional control and a good superficial finishing, but requires good decision making and ability from the machine operator (Bianchi et al., 2003; Xiu et al., 2005). The grinding characteristics of advanced ceramics are very much different from the ones for metals and, therefore, it is necessary to perform further studies to achieve a more comprehensive understanding and a better control of the parameters in order to achieve good surface finish. The finish produced on the workpiece surface is one of the most important parameters in finish grinding (Agarwal and Rao, 2005).

Despite various research efforts in ceramic grinding over last two decades, much needs to be established to standardize the theoretical models for the prediction of surface roughness for improving product quality and increasing productivity to reduce machining cost. The effective use of ceramics in industrial applications demands the machining of ceramics with good surface finish and low surface damage. In order to assess the effectiveness of ceramic grinding, experimental or theoretical evaluation of surface roughness is essential. But, the experimental methods of surface finish evaluation are costly and time consuming. So, an attempt has been made to develop a theoretical model for the prediction of surface roughness for the grinding automating this process (Agarwal and Rao, 2005; Xiu et al., 2005)

One way to improve the process is to estimate the surface roughness by monitoring the signals from the grinding process. Some process variables such as material removal emit signals that can be measured and studied, measurement of vibration, for example, as regards oscillatory motions bodies and their strengths that are associated with the movement frequency. The extracted signal of vibration measurement can be studied using analytical methods and spectral estimation and correlate with the process conditions (Teti et al., 2010; Zeng and Forssberg, 1994).

Considering the importance in ceramic grinding for the industry and also the relevance for analyzing the quality of its surface, this work aims to continue the research of Oliveira et al. (2015), which sought to find a correlation between the surface roughness and the RMS (Root Mean Squared) of the vibration signal. The objective of this paper is to study the vibration signal by using spectral analyses obtained by Pwelch method towards monitoring the grinding process, testing the ability of the vibration signal to follow the changes of workpiece surface roughness.

2. LITERATURE REVIEW

High performance ceramic components have gained importance in recent years. Because of their good properties such as hardness, resistance to temperature and wear, these components are increasingly being applied in automotive and manufacturing industries (Huang and Liu, 2003). However, the actual utilization of advanced ceramics has been quite limited mainly because of the high cost of the machining these materials by grinding while ensuring the workpiece quality. A technological basis to achieve more efficient utilization of the grinding process for ceramics requires an understanding of the interaction between the abrasive and the workpiece which has direct bearing on the surface finish produced. Extensive research has been carried out to predict the surface roughness of the workpiece manufactured by grinding (Malkin and Guo, 2008).

Among other applications such as in the nuclear industry and satellites, ceramic workpieces are also applied. Besides others, applications in bearings for nuclear use of ultra-accuracy mechanic and satellites should be noted; the same applies automotive pieces (sensors, insulators, catalyzers, pistons, jackets, inserts, valves, linings), biocompatible implants (coxofemoral and dental prosthesis, bone replacement, cardiac valves), parts that can wear out (valve seat, mechanical seals, guides), refractories (insulators rocket lining plates, military linings, furnace components), substrates, bases and insulators in electric components (Bianchi et al., 2003).

The manufacturing process of these workpiece involves powder compaction, followed by machining, sintering and final machining using abrasive processes (Inoue et al., 1989). The abrasive machining involves grinding, polishing and lapping with abrasive diamond. The high cost of machining is the main obstacle to large-scale ceramic industrial manufacturing (Xu and Jahanmir, 1994) thus, it is expected to increase the machining rates without damaging the mechanical properties of the product. However, to achieve this, it is necessary to understand the material removal mechanism on a micro structural scale and the relation between the micro structure and the formation of a damaged layer by the machining process.

The grinding process, the most important step of the advanced ceramic machining process, is highly complex and involves the contact between a large numbers of abrasive particles with the surface of the workpiece. The grinding process allows a precise dimensional control, and a good superficial finishing, but requires ability from the machine operator, and the decision making concerning the final quality. Furthermore, the grinding characteristics of advanced ceramics are very different from the ones for metals (Mayer and Fang, 1993), and it is still necessary to perform further studies to achieve a more comprehensive understanding and a better control of their parameters; studies in this regard have already been made. The understanding of the material removal mechanisms and its consequences in the mechanical properties, cost and surface quality is extremely important for the advanced ceramic manufacturing, in which failures like superficial and internal cracks, non-uniform voids, shapes and sizes of grains, act as tension amplifiers, making ceramic products fracture at tensions below the acceptable level (Bianchi et al., 2003).

On the other hand, the surface roughness is influenced by the grinding processes which become an essential aspect to be analyzed at industrial applications such as metals processing and fabrication, semiconductor manufacturing, ceramics, paper and plastic. Despite the importance of a microscopic surface evaluation of the parts, the surface roughness is measured, in many cases, by using traditional methods with rod and optical profilometry. This continuous acquisition becomes impractical in a production line due to the constant pause of the machine for measuring the surface roughness (Dhanasekar et al., 2008; Whitehouse, 2010).

Surface roughness is the most important factor to evaluate the quality of machined workpiece. At the end of the process, the surface finish affects the characteristics of the workpiece, which include fracture and fatigue strength, as well as surface roughness (Samhouri and Surgenor, 2005). The surface roughness, R_a, is defined as the arithmetic average of the absolute values of the deviations of the surface profile height from the mean line within the sampling length *l*. Therefore, the surface roughness Ra can be expressed as:

$$R_a = \frac{1}{l}\int_{y\,min}^{y\,max}|y - y_{c1}|p(y)dy \qquad (1)$$

Where y_{c1} denotes the distance of the center line, drawn in such a way that the areas above and below it are equal. The y_{max} and y_{min} are the lowest and highest peak height of the surface profile and *p(y)* is the probability that height of grain has a particular value y (Agarwal and Rao, 2005).

Predicting and identifying surface roughness is the object of study of many researchers. Samhouri and Surgenor (2005) state that monitoring of the grinding process serves to detect problems, provide information to improve and control the process, and lastly, contribute toward establishing parameters that are necessary to determine the best operating conditions. The need to enhance equipment components, improving their application in given environments, has resulted in the use of new materials. Technological advances in the production of ceramic materials have made it possible to apply techniques that were previously utilized with metals. Thus, phase transformations, alloys, and tempering and annealing techniques have been employed in a wide range of ceramics.

According to Agarwal and Rao (2005), despite various research efforts in ceramic grinding over last two decades, much still needs to be done to standardize theoretical models for predicting surface roughness, thus improving the quality of the product and increasing productivity in order to reduce manufacturing costs. However, automated measurement of surface roughness during the grinding process is still difficult to apply. Some systems use laser, but they are expensive and unsuitable for the grinding environment.

Direct analysis of the workpiece surface requires that the machine be stopped, and the tool extracted and visually inspected, which result in machine downtime and human user intervention cost. Indirect methods of analysis, however, allows for a monitoring without shutting down the machine and interrupting the production process, This can be achieve by acquiring sensor signal, digital processing, and feature extraction, Indirect methods that rely on the relationship between tool conditions and measurable signals (such as vibration signal, for example) for detecting tool conditions have been extensively studied (Zhou et al., 2011).

According to Teti & ciclano (2010), vibrations that occur during metal cutting can be divided into two groups: (i) dependant and (ii) independent of the cutting process. The two groups are not mutually exclusive. Vibration independent of metal cutting include forced vibration caused by other machines or machine components, e.g. vibration transmitted through foundations, unbalance of rotating parts, inertia forces of reciprocating parts and kinematic inaccuracies of drives. Vibration dependent on metal cutting can demonstrate a number of characteristics as a function of the process, e.g. interrupted cutting. The varying cutting forces that occur during metal cutting may result from non-homogeneity and properties variations in the work material. Tool engagement conditions during machining play a notable role in the vibration produced. The self excited vibration characteristic known as chatter is the most renowned type of vibration in machining and is detrimental to surface finish and tool life.

Spectral analyses are an efficient method to be applied for study vibration signals. They are based on selecting frequencies bands that will characterize the physic variable which is desirable to control or estimate (Zeng; Forssberg, 1994). One of the used methods on signal frequency analysis is the Fast Fourier Transform (FFT). The FFT is an algorithm that implements Discrete Fourier Transform (DFT) efficiently, reducing the calculus and the processing time.

Spectrum estimation of discretely sampled processes is usually based on procedures employing the FFT. This approach is computationally efficient and produces reasonable results for a large class of signal processes. In spite of the advantages, there are several performance limitations of the FFT approach. The most prominent limitation is that of frequency resolution, i.e. the ability to distinguish the spectral responses of two or more signals. To alleviate the limitations of the FFT approach, many new spectral estimation methods, such as parametric methods, have been proposed during the last decades (Cichocki and Lobos, 1994; Lobos et al., 2001).

In this study, the signals are analyzed by using their PSDs. There are several methods to estimate the PSD. Non-parametric methods are those in which the estimate of the PSD is made directly from the signal itself. The simplest one is known as a ‘‘periodogram’’. The Welch method is an improved version of the periodogram (Mathworks, 2002; Welch, 1967).

The Welch method is a periodogram method used for determining the power density of the frequency components in a signal based on the Fourier transform. To obtain the PSD of a signal by the periodogram method, it was divided into frames as 64, 128 and 256, which are powers of 2. To evaluate the power spectrum, this method divides the data into several overlapping segments, computes a power spectrum by using a FFT on each segment and then averages these spectra (Semmlow, 2004). The Welch periodogram consists of the average of the original periodograms for all segments *P* considered by the window *w(n)*, Calculating the original periodogram p - th segment , according to (2):

$$\hat{P}_w(f) = \frac{1}{p}\sum_{p=0}^{p-1}\breve{P}_{xx}^{(P)}(f) \quad (2)$$

Where $f = fs$ is the normalized frequency variable having units of cycles per sample. $P_{x,x}$ is an estimator for the PSD of time series x(n) at frequency *f*. The welch method parameters can be manipulated in order to obtain series of estimates by using another equations. For more information about the method can be found in works of (Alkan and Yilmaz, 2007; Welch, 1967; Zhang et al., 2014).

3. MATERIAL AND METHODS

The grinding experiments were performed on a surface grinding machine using a resin-bonded diamond wheel (Dinser SD126MN50B2, 350 mm diameter). The grinding and dressing conditions were established based on the experience gained by the Abrasive Machining Group, and the main parameters are described in Table 1. The workpieces were alumina base blocks with a length of 20 mm along the grinding direction and a width of 8 mm corresponding to the grinding width. The cutting fluid was a water–oil emulsion of 4% concentration, using DMS 3200 F-1 oil manufactured by Shell. The concentration of the cutting fluid was measured using a portable ATAGO N-1E refractometer. The grinding wheel was sharpened using an aluminum oxide sharpening tool to wear down the binder and expose the grain, thereby increasing its cutting potential. Table 1 lists the parameters adjusted to the system.

Table 1. Machining Parameters of the Tests

Processing Speed		**Cooling Specifications**	
Peripheral Speed of the Grinding Wheel (Vs)	35 m/s	Type of Fluid	Conventional, Water and Oil Emulsion
		Cooling Fluid	Rocol Ultracut 370
		Concentration	5%
Workpiece speed, table (Vw).	58 mm/s 125 mm/s	Fluid velocity	3m/s
		Fluid Outflow from the Rectangular Nozzle	27.5l/min
		Pressure of Fluid in the System	Lower than $0.2 kgf/cm^2$

The acquisition of the vibration raw signal was made through an accelerometer stuck to the workpiece support. The sensor, model 353B03, was connected to an amplifier unit, model 482B11, both from PCB Piezotronic. The signal was collected using a Yokogawa DL850 oscilloscope, at a sampling rate of 2 MHz. For measuring the surface roughness it was used a Taylor Hobson Surtronic 3+ surface roughness tester. During the tests, surface roughness was measured at four programmed stops, adopting R_a parameter.Tests were performed at three different cutting depths: 25µm, 105µm and 350µm, and the other grinding parameters were kept constant. The volume of material removed from each workpiece during the tests was constant. The grinding wheel was dressed prior to each test. Fig. 1 illustrates the experimental setup, surface roughness measurements and signal processing following the tests.

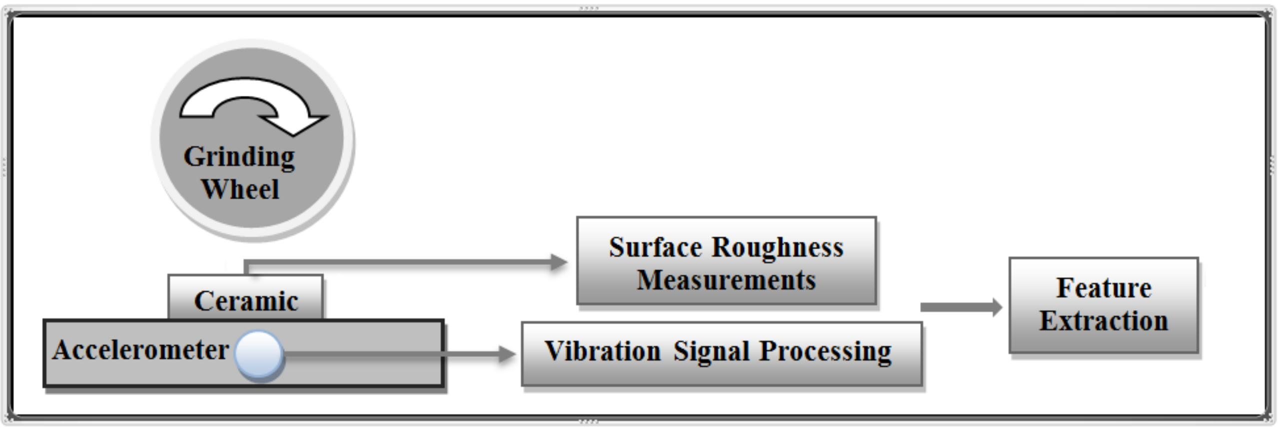
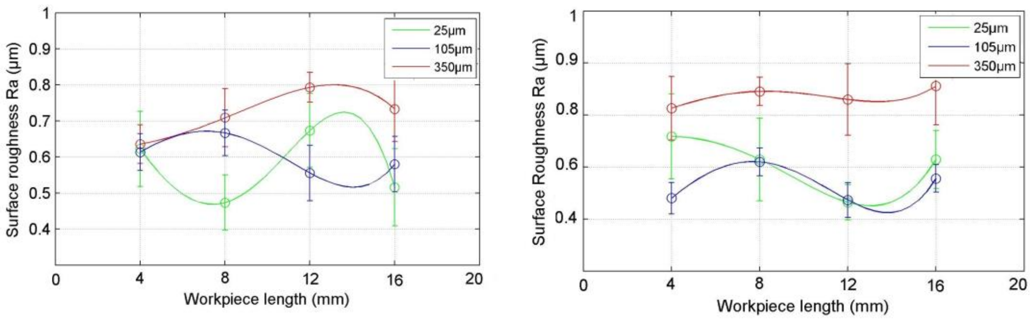


Fig 1. Data Acquisition and Signal Processing Scheme

The vibration signal was recorded in each pass. The vibration signals from the grinding process were processed and the PSD obtained, using the Welch's method with an 8192-point Hanning window with a 50% overlap, implementing Pwelch function in MATLAB. As it can be seen in table 1, the experiments were carried out for two different cutting speeds in order to obtaining mild to severe grinding conditions and, consequently, to better study the correlation between vibration signal and surface roughness.

4. RESULTS AND DISCUSSION

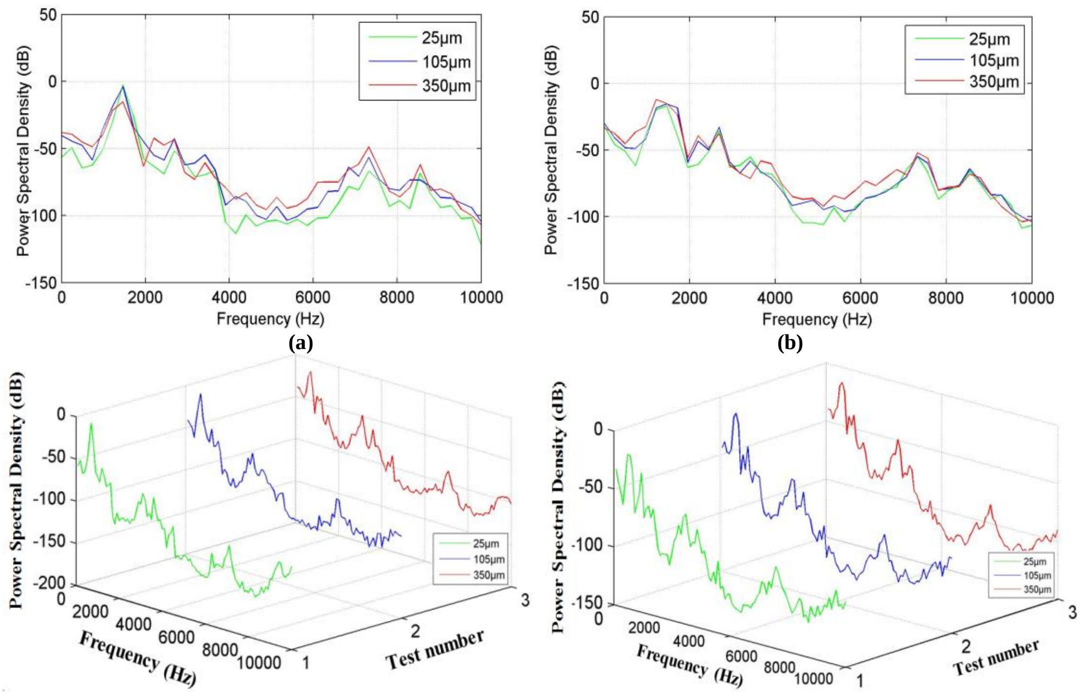
In fig 2, the measurements of surface roughness for different workpiece speed used in the tests were interpolated to facilitate the analysis. As can be seen in this figure, surface roughness values are higher for depth of cut 350μm for both workpiece speed, as expected. On the other hand, the values for 25μm and 105μm are nearly the same and with certain variation along the workpiece length. The higher the workpiece speed the higher is the surface roughness, which is also expected due a more aggressive grinding condition. Also, it can be noted high values of standard deviation, which are generally usual for roughness measurements. However, all surface roughness values fell in the ranges used in the grinding process.



(a) **(b)**

Fig 2. Mean of surface roughness R_a against workpiece length; v_w=58 mm/s (a); v_w=125 mm/s (b).

Figure 3 shows the spectral of vibration signal obtained by PSD, which represents different characteristics for each test, according to the depth of cut. These signals are interesting for study because the three depth of cut are precisely defined along the frequency domain. The signal follows a tendency on the graph and has lower amplitude for 25μm, as expected. It is possible to observe that when the depth of cut is higher, the level of vibration is in general higher for all frequency bands. Peaks in the PSD curves may indicate the presence of some periodic components related to surface roughness.

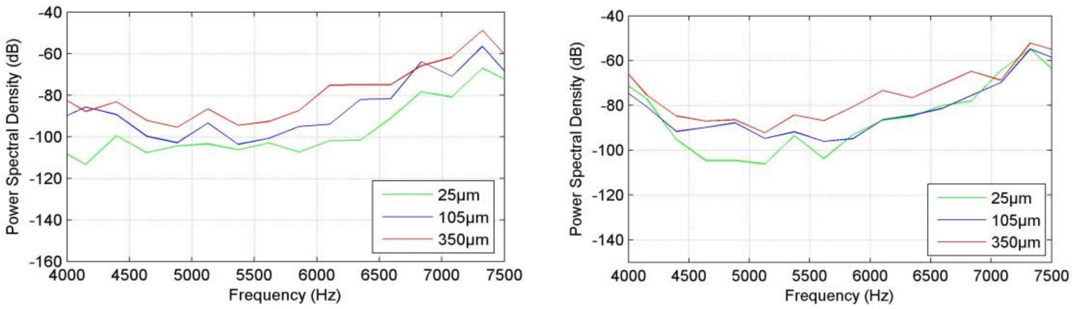


(c) **(d)**

Fig 3. PSD vibration signal; v_w=58 mm/s (a) e (c); v_w=125 mm/s (b) e (d);

Importantly, the dynamic characteristics such as the natural frequency and mode shapes of the surface grinder were determined based on the following statements: Reddy (2015) uses a modal analysis to determine the vibration characteristics (natural frequencies and mode shapes) of a structure or the machine component while it is in operation. According to Reddy (2015) the modal analysis for surface grinder shows the frequency is at the increased each iteration. This range of natural frequency varies from 48,977 Hz to 79,968 Hz. In research Oliveira et al (2008) experiments were carried out to observe the influence of vibrations in the wheel wear. Several forms of vibration were applied to the part in preliminary experiments. These included sinusoidal vibrations at the natural frequencies, wheel rotation frequency (to simulate unbalancing) and also random noises. The response frequency curve was measured and natural frequencies of 125, 205 and 300 Hz were found.Thus, it is inferred that, the natural frequencies found in surface grinding machines are below 1 kHz, based on the study of the dynamic behavior. Thus, the frequencies ranges obtained from the spectral analysis of this study are from the process.

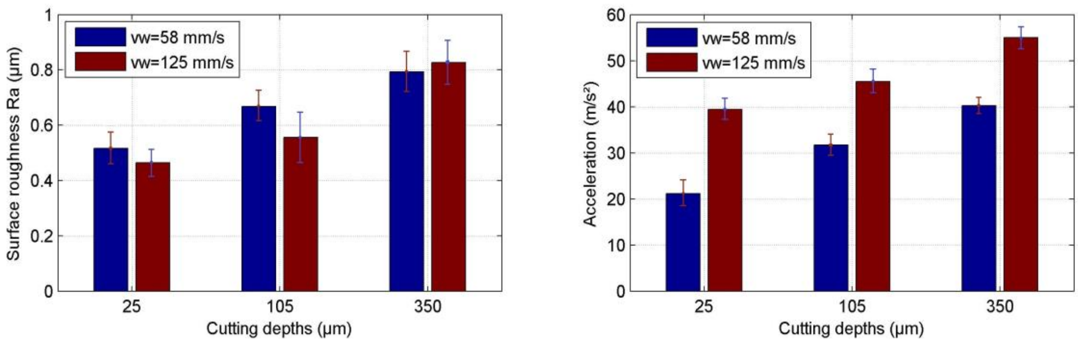
Figure 4 presents a magnification of graph shown in Fig. 3 for the frequency range of 4 kHz to 7.5 kHz, with the aim of analyzing details in the vibration spectra where the differences among the three grinding conditions are more significant. It is possible to note that the Welch method is sensible to the samples resolutions, and also that it is very perceptible to see the frequencies bands well defined (no overlapping) such as from 5500 Hz to 6500 Hz (a) and from 4500 Hz to 6000 Hz (b). Other visible aspect of these frequency ranges is the increasing behavior of the signals for each grinding condition.



(a) **(b)**

Fig 4. PSD vibration signal, in frequency band of the 4000 to 7500 Hz; v_w=58 mm/s (a); v_w=125 mm/s (b).

Figure 5 shows graphs for comparison between the surface roughness and vibration signal. It can be seen that the behavior of surface roughness values increase as the cutting depths increase, for both workpiece speed studied. The same behavior is observed for the vibration signal (acceleration), which also increases as the depth of cut increases. However, it can be observed the inverse correlation between surface roughness and vibration signal with regard to the workpiece speed. As roughness values are higher for the workpiece speed of 58mm/s, the vibration values are lower for this workpiece speed. This can be explained by the time elapsed in the grinding pass, which is longer for the lower speed and, in turn, the grinding wheel grits are kept in contact with the workpiece during a longer period of time, generating a worse surface finish as well as a lower level of vibration.



(a) **(b)**

Fig 5. Surface roughness (a) and vibration (b) for three different cutting depths and two workpiece speeds.

5. CONCLUSION

Based on the results obtained in this work, it can be concluded:

- The surface roughness values remained within an acceptable standard, according to the literature, as can be seen on values of standard deviation.

- The higher the depth of cut the higher is the surface roughness, considering only the average value. So does the vibration values. Concluding that increased the severity of the grinding process, surface roughness and vibration increase.
- From the vibration signal of the PSD, frequency bands was identified, between 4 kHz and 7.5 kHz, that defines in ascending order the signal in the three non-overlapping cutting depths. Showing that the vibration increases as the cutting depth is greater.
- A monitoring system for low-cost real-time can be proposed since the available frequency bands of vibration are below 10 kHz.

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7. REFERENCES

Agarwal, S., Rao, P.V., 2005. A probabilistic approach to predict surface roughness in ceramic grinding. Int. J. Mach. Tools Manuf. 45, 609–616.

Alkan, A., Yilmaz, A.S., 2007. Frequency domain analysis of power system transients using Welch and Yule–Walker AR methods. Energy Convers. Manag. 48, 2129–2135.

Bandyoupadhyay, B.P., 1995. The effects of grinding parameters on the strength and surface finish of two silicon nitride ceramics. J. Mater. Process. Technol. 53, 533 – 543.

Bianchi, E.C., Aguiar, P.R., Silva, E.J., Silva, J., Fortulan, C.E., 2003. Advanced ceramics: evaluation of the ground surface. Cerâmica 49, 174–177.

Cichocki, A., Lobos, T., 1994. Artificial neural networks for real-time estimation of basic waveforms of voltages and currents. IEEE Trans Power Syst 9, 612–8.

Hu, K.X., Chandra, A., 1973. A fracture mechanics approach to modeling strength degradation in ceramic grinding processes. Trans. ASME, J. Eng. Ind. 115, 73–84.

Huang, H., Liu, Y.., 2003. Experimental investigations of machining characteristics and removal mechanisms of advanced ceramic sin high speed deep grinding. Int. J. Mach. Tools Manuf. 43, 811–823.

Inoue, M., Kihara, Y., Arakida, Y., 1989. Injection mouldingmachine for high performance ceramics. Interceram 2`89, J.Ceram. Rev. 2 53–57.

Lobos, T., Kozina, H., Koglin, H., 2001. Power system harmonics estimation using linear least squares method and SVD. IEE Proc Gener. Distrib. 72, 148–577.

Malkin, S., Guo, C., 2008. Grinding technology: theory and aplications of machining with abrasives, 2ª ed. New York.

Mathworks, T., 2002. Signal Processing Toolbox for Use with Matlab, User's Guide, V6 ed.

Mayer, J.J.E., Fang, G.P., 1993. Diamond grinding of siliconnitride. NIST SP 847 205–222.

Oliveira, P. C. J., Ribeiro, D. M. S., Rodrigues, A. C., Aguiar, P. R., França, T. V., Bianchi, E. C., 2015. Monitoramento da retificação de cerâmicas avançadas por sinais de vibração e rugosidade. In: VIII Congresso Brasileiro de Engenharia de Fabricação - COBEF. Salvador -BA. v. 8. P.1-10.

Oliveira, J. F. G., França, T.V., Wang, J. P., 2008. Experimental analysis of wheel/workpiece dynamic interactions in grinding. CIRP Annals - Manufacturing Technology 57 (2008) 329–332.

Reddy, R., 2015. Analisys of resonance of a surface grinder. Department of Mechanical Engineering, BKIT ,Bhalki, Karnataka, India. Indian J.Sci.Res. 11, 046-053.

Samhouri, M.S., Surgenor, B.W., 2005. Surface roughness in grinding: on-line prediction with adaptive neuro fuzzy inference system. Trans. NAMRI/SME 33, 57–64.

Semmlow, J., 2004. Biosignal and biomedical image processing MATLABbased applications. Marcel Dekker Inc.

Teti, R., Jemielniak, K., O'Donnell, G., Dornfeld, D., 2010. Advanced monitoring of machining operations. CIRP Ann. - Manuf. Technol. 59, 717–739.

Welch, P.D., 1967. The use of fast Fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms. IEEE Trans. Audio Electroacoust.

Xiu, S.C., Li, Q., Cai, G.Q., Li, C.H., Gong, Y.D., 2005. Key technology and mechanism of CNC quick-point grinding. J. Harbin Inst. Technol. (New Ser. 12, 43–46.

Xu, H.H.K., Jahanmir, S., 1994. Simple technique for observingsubsurface damage in machining of ceramics. J. Am. Ceram.Soc. 77 1388–1390.

Zeng, Y., Forssberg, E., 1994. Monitoring Grinding Parameters By Vibration Signal Measurement - A Primary Aplication 7, 495–501.

Zhang, J., Yuan, Z., Huang, J., Yang, Q., Chen, H., 2014. Quantification of the power changes in BOLD signals using Welch spectrum method during different single-hand motor imageries. Magn. Reson. Imaging 32, 1307–1313.

Zhou, J.H., Pang, C.K., Zhong, Z.W., Lewis, F.L., 2011. Tool wear monitoring using acoustic emissions by dominant-feature identification. IEEE Trans. Instrum. Meas 60, 547–559.

8. RESPONSIBILITY NOTICE

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