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Using the Wavelet Transform in an Indirect Predictive Approach to Monitor the Surface Quality in Grinding

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Abstract- **Production systems are currently under high constraints of availability, productivity, quality and flexibility. Therefore, it is a necessary to monitor and to keep operational the entities of the manufacturing process. In this paper, we are interested in solving some problems with the temporal component, like the periods to change used tools, in order to optimize the tasks on line. For this reason, a set-up of indirect predictive monitoring strategy online has been realized to follow-up the evolution of surface quality of the workpiece. In fact, the detection of the workpiece state after grinding in real time can help to avoid production downtime during the quality control, exhaustive damage of machined quality workpiece and machining system. In addition, a frequent change tool or plate not monitored induces additional costs. In this context, several studies have been conducted to propose methods and techniques for monitoring surface quality of the machined workpiece. In the most of cases, the developed approaches have used indirect measures of the state of the cutting tool. The measured signals will be analyzed later by the different techniques of signal processing to extract the information about the state of the cutting tool. In second stage, a correlation between the state of the cutting tool and the machined surface quality is established. However this double treatment can generate errors which can be at the origin of a divergence between the acquired signal by the sensor and the real state of the surface quality. It is in this context that the work presented in this paper is to develop a unique treatment to establish a direct correlation between the signals obtained by a sensor of cutting force in grinding and the surface quality of the workpiece. The wavelet decomposition is used in this paper to treat these signals.**

Index Terms—**Indirect monitoring, Detection, discrete wavelet transform, grinding, the cutting force in grinding**

1. INTRODUCTION

Actually, it is essential that the performances, the indicators and the characteristics of the system are monitored in order to detect any abnormal operation. Achieving this objective requires the enhancement of the monitoring function in industry. Indeed, in the context of preventive conditional predictive maintenance, the basic principle of monitoring is to evaluate the behaviour of a degraded system by monitoring the disruption generated on the products. In this context, we present a set of the means used in monitoring to observe the state of the quality of the machined surface (in real time) in order to cope with the alias of the system during the grinding process. Generally, monitoring function is defined by Basseville [1] as a combination of two phases: detection and diagnosis; the first is based on the acquisition of the data sensors from the system and provides to the operator more or less elaborate information according to the detection system. The second phase includes the location and identification of defects that constitute the diagnostic phase. This type of monitoring is commented by Racoceanu [2] as the traditional monitoring. Racoceanu treated another type of monitoring called the dynamic monitoring also named predictive. As for the traditional monitoring, the predictive monitoring is composed of predictive detection (dynamic) and the predictive diagnosis, also called prognosis. The first phase consists in predicting a future failure. In other words, the aim of predictive detection is to detect degradation instead of a failure and second is to identify the causes and to locate the component that involves a particular degradation. Our target is to identify the degradations, related to the qualitative or quantitative variation of intrinsic aptitudes of a grinding process. This identification is carried out by the analysis of the deviations on the surface quality of the products. Nabli [3] presented in its work a systemic analysis of the monitoring function on which we will base ourselves for the indirect predictive monitoring.

2. A SUGGESTED MONITORING APPROACH

In general, a good monitoring approach is based on four principal components: the follow-up of system evolution by extraction signals that are pertinent to the monitoring, the detection of the drifts, the diagnosis and prognosis (Fig1).

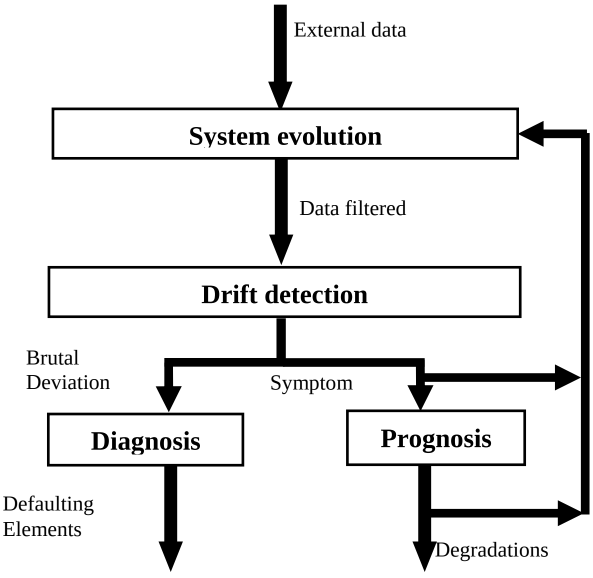

Fig. 1. A global approach for monitoring

In majority of work the follow-up of system evolution is divided into two stages; in the first step, to extract information concerning the state of a cutting tool from the signals taken on sensors and in the second step to establish a correlation between the state of the cutting tool and the surface quality of the machined workpiece.

In the case of grinding process, several techniques were developed in the literature in order to follow-up the system evolution. These techniques are based on: Intelligent system

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[4,5 and 6], sound emission [7,8] and vibration [9]. Mokbel and Maksoud [10], Susic and Grabec [11], applied the technique of the acoustic emission to show that we can use it to monitor the state of the grinding stone diamond during the ceramics grinding. On the other hand, the establishment of a correlation between the state of the grinding stone and the surface quality make it possible to use this technique like indirect monitoring means of the surface quality.

Monitoring by intelligent systems is the subject of several studies. Lezanski [12] used the neural networks and fuzzy logic for the monitoring of the state of the grinding stone in external cylindrical grinding. This system has an advantage when the number of variables of entry is important, but it presents a limitation compared to the neural networks from the point of view reliability of information.

Hassui et *al.* [13] showed that the quadratic average of the signal of vibration of the machined part presents the wear of the grinding stone. They examined in another work [14] the capacity of the signal of vibration to follow the change of the roughness of surfaces of the machined surface. However this double treatment can generate errors that can be at the origin of a divergence between the acquired signal by the sensor and the real state of the surface quality (Fig 2).

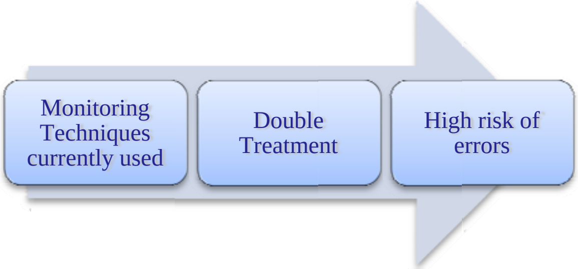


Fig. 2. The follow-up of system evolution

The surface quality obtained by this process depends on some parameters such as: cutting force, absorptive power and the state of the grinding stone. The cutting force in grinding is broken up into two principal components: normal grinding force F_n and tangential grinding force F_t. Indeed, it was shown that the normal component has an influence upon the surface deformation and roughness of the workpiece, the tangential component controls the power consumption, the heat flux at the contact zone between the grinding wheel and the workpiece, the gradient of the residual stress and the wear of the abrasive grains [15]. In this paper, the monitoring approach consists in developing a single treatment able to establish a direct correlation between the measured signals obtained by a sensor of cutting force of type Kistler 9257B in grinding and the micro-geometrical quality of the surfaces finished by this process. Then, in the case of the detection of a drift on the level of measurement, decline in the quality micro geometry of the surface, we suppose that it is related to the state of the cutting tool. We define in this case a measurement indicator of performance which is compared to the allowable intervals representing the surface quality, in order to detect degradation in the state of the cutting tool.

The tool most used for the treatment of the signal is the Fourier transform. Thus, the signal can be transformed from the time domain to the frequency domain. Often, the information that cannot be easily seen in the time-domain can be seen in the frequency domain. For a non-stationary signal, the signal parameters (frequency content etc.) evolve over time. The standard Fourier Transform is not useful for analyzing the signal, like our case. It is very difficult to tell us when detecting degradation in the state of the cutting tool from the frequency domain. In recent year, another approach, called Wavelet Transform, was developed in order to decompose the signal into various components at different time windows and frequency bands [16, 17 and 18]. In machining, this technique was applied for the detection of the cutting tool failure, especially tool breakage [19, 20], and for the analysis of machine tool vibration.

2.1 The discrete wavelet transform

The wavelet transform of a signal $f(t)$ is defined as the integral over time of $f(t)$ multiplied by the scaled and shifted versions of the wavelet function $\psi(t)$.

This transform generates coefficients C (a, b) called "The wavelet coefficients" that are expressed as follows [16]:

$$C(a,b) = \int_{-\infty}^{+\infty} f(t)\frac{1}{\sqrt{a}}\psi(\frac{(t-b)}{a})dt \qquad (1)$$

where a is the scaling parameter and b the shifting parameter.

For the numerical signals $f(t)$, we use the discrete wavelet transform which is defined as follows [16]:

$$C(j,k)=C(a,b)\backslash_{a=2^j,\, b=k2^j} \qquad (2)$$

The wavelet coefficients C (j, k) represent the amplitudes of the wavelet used in the decomposition of the signal; these coefficients can be divided into two parts: the approximation coefficients (cA) and the detail coefficients (cD). By using these wavelet coefficients, we can rebuild the original signal $f(t)$. These coefficients can be expressed as follows [16]:

$$cAj= \sum_{m=0}^{\infty} f(m)\emptyset_{j,k}(m) = \sum_{m=0}^{\infty} f(m)\frac{1}{\sqrt{2^j}}\emptyset(\frac{m-k2^j}{2^j}) \qquad (3)$$

where $\phi_{j,k}(m)$ represents the scale function.

$$cDj= \sum_{m=0}^{\infty} f(m)\psi_{j,k}(m) = \sum_{m=0}^{\infty} f(m)\frac{1}{\sqrt{2^j}}\psi(\frac{m-k2^j}{2^j}) \qquad (4)$$

where $\psi_{J,k}(m)$ represents the wavelet function.

The index j represents the level of the decomposition in the discrete wavelet transform. The choice of the suitable level j depends on the length of the signal and the task to be carried out. On each level j, we build the approximation called A_j by taking account of the "low frequencies" of the preceding level of the approximation and the detail called D_j which corresponds to the "high frequencies". (Fig 3)

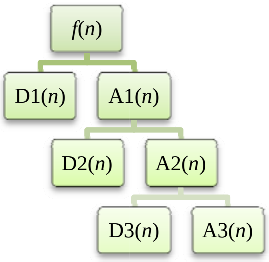


Fig 3. Structure of the signal decomposition

This decomposition can be iterated, the approximations being decomposed successively: this is called the multilevel wavelet decomposition.

2.2 Statistical Analysis

The statistics are used for analyzing and interpreting the data contained in the signals. At the beginning, we note that it is difficult to establish a correlation between the rough signal of the cutting force and the roughness of grinding surfaces. After the decomposition of the signal, several statistical parameters are used and compared to highlight the existence of this correlation. The parameters used are the average, the standard deviation, the absolute deviation of the median and of the average. These parameters are described by the following equations:

2.2.1. The average

For a data set, the average is described as the sum of all the observations divided by the number of observations. In the case of the signal of grinding force, the average was established from the detail coefficients of the maximum level j (given according to the signal size). It is expressed by the following expression:

$$\overline{cD_j} = \frac{1}{N}\sum_{k=1}^{N} cD_j\,(k) \qquad (5)$$

2.2.2. The standard deviation

The standard deviation is measured from the average difference between the values of the data in the set. It is expressed as follows:

$$S = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}(cD_j(k) - \overline{cD_j})^2} \qquad (6)$$

2.2.3. The absolute deviation

The absolute deviation of an element of a data set is the absolute difference between this element and a given point. Typically the value of the point from which the deviation is measured, is the value of either the average or the median of the data set. The average absolute deviation of a set {cDj (1), cDj (2) ... cDj (N)} is expressed by:

$$AD = \frac{1}{N}\sum_{k=1}^{N}\left| cD_j(k) - \widehat{cD_j} \right| \qquad (7)$$

Where cDj (K) is an element of the detail coefficients at level j and cD_j is the measurement of the average or the median of the details coefficients at the level j.

3. EXPERIMENTAL PROTOCOL AND ALGORITHM OF WAVELET DECOMPOSITION

The machine used is a plane grinding machine SR RT600 having two automated axes (vertical and horizontal) and a transverse axis at constant speed. The fluid of lubrication used is the “SMILAX 89” (concentration 20% and 80% of water). The dressing of the stone was ensured by a single diamond. Transverse speed corresponding at the speed of rising was varied by using a motor step by step. To obtain the signals of grinding force, a dynamometer Kistler 9257B with three components was used to measure the three components of the force. This dynamometer has a high rigidity and therefore a high frequency; the high resolution makes it possible to measure the least variations of effort. The signal emitted by the dynamometer is amplified using a charge amplifier which transforms the signals of the dynamometer into output voltages proportional to the forces applied. Then, these efforts are acquired on a PC. The samples are prismatic form of dimension 15 × 15 × 50mm and have undergone a heat treatment of relieving (maintains with 1100°C during one hour followed by a cooling with the air) before carrying out the grinding tests. The material used is a stainless steel austenitic X5CrNiMo18-08.

The general algorithm of this transformation is represented in fig 4.

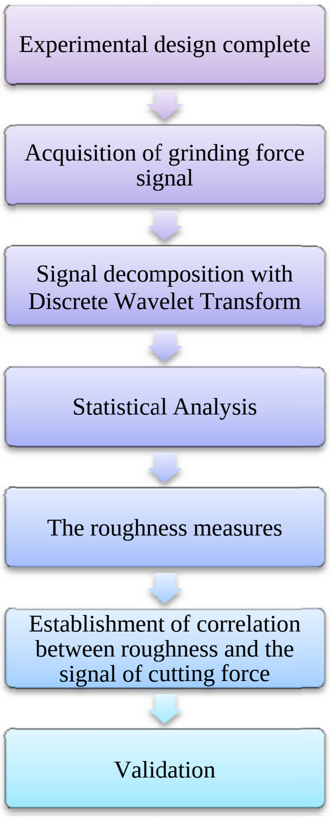


Fig. 4. Algorithm for the decomposition of the grinding force.

The experiments were realized according to an experimental design of 54 tests for which the factors and their associated levels are given in the grinding stone used is a type of 95A60H

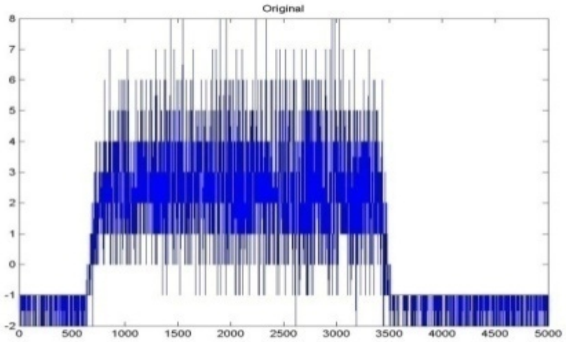
Table 1. Summary table of the factors and their levels

	Grain of the grinding stone **#**	Table speed [m/mn] **Vw**	Speed of raising [m/s] **Vd**	Depth of cut [µm] **a**	Numbers of cut **Np**
Level 1	60	1	8.2	5	10
Level 2	60	8	4	10	20
Level 3	60	14	2	20	-

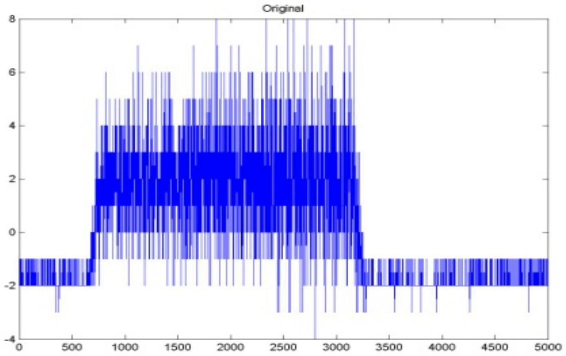
In this study, the discrete wavelet transform employs those of Daubechies [19] for the multilevel signal decomposition of the cutting force.

4. RESULTS AND DISCUSSION

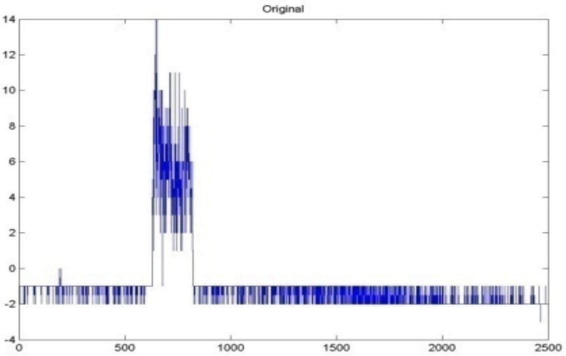
In this study, we record the 54 tests (signals) starting from the normal component F_n of the grinding force (considering this component has an influence on the surface deformation and the surface quality of the rectified parts). Fig 5 shows the signals of some tests n°5-11-49 obtained under various grinding conditions. We note that during grinding, the presence of several peaks in the signals which are not constant and due to a great variation of amplitude.



Test N°05:
Vw: 1 m/mn; **Vd:** 8,2 m/s; **a:** 20µm; **Np:**10.



Test N°11:
Vw: 1 m/mn ; **Vd:** 4 mm/s; **a :** 20µm ; **N_p :**10.



Test N°49:
Vw: 14 m/mn; **Vd:** 2 m/s; **a:** 5µm; **Np:**10.

Fig. 5. Examples of cutting force signals measured under various grinding conditions

These variations do not indicate anything like useful information on quality rectified coins, for example starting from the signals of fig 5 it is difficult to know, after grinding, if the coins have same surface quality or not. Indeed, these signals indicate only the point of engagement of the tool in the matter which is translated by an increase in the signals and the point of release which is represented by a reduction. To draw more information starting from these signals, a treatment is necessary in this case. The characteristic of these signals is that they are not stationary. As the traditional techniques are not able to treat this kind of signals, we chose to use the technique of the discrete wavelet transform.

In our case, Daubechies wavelet of order 3 (db3) is used since it detects better the abrupt changes of frequency in the signal. In addition, this wavelet is orthogonal what makes it possible to make a multi level analysis of the various signals of the cutting force. The scale function and the wavelet function for db3 are shown in fig 6.

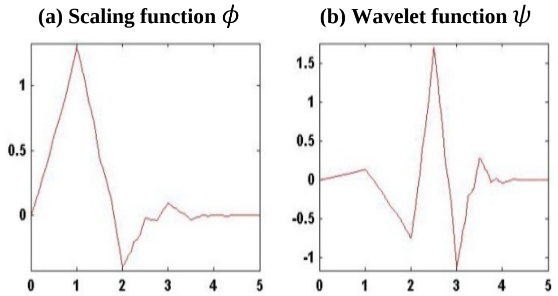

(a) Scaling function ϕ **(b) Wavelet function ψ**

Fig. 6. The wavelet db3 (a) the scaling function ϕ ; (b) the wavelet function ψ

Fig 7 shows the structure of the signal decomposition in several levels. We choose test N°17 as example, the sample size (n) during the recording of this signal is 5000. According to the sample size, we can reach the level 9 in the decomposition of this signal without any loss of information. Beyond this level, there has a risk which we cannot find information concerning the surface quality of the rectified parts.

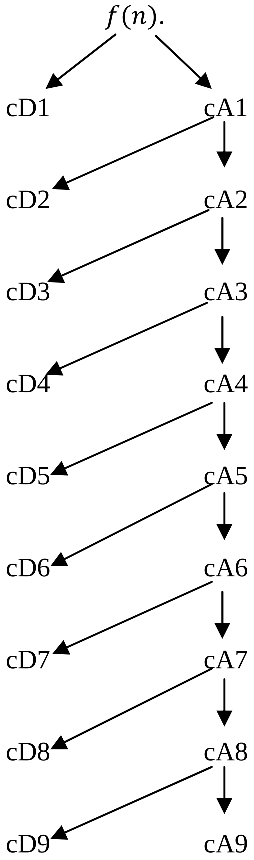
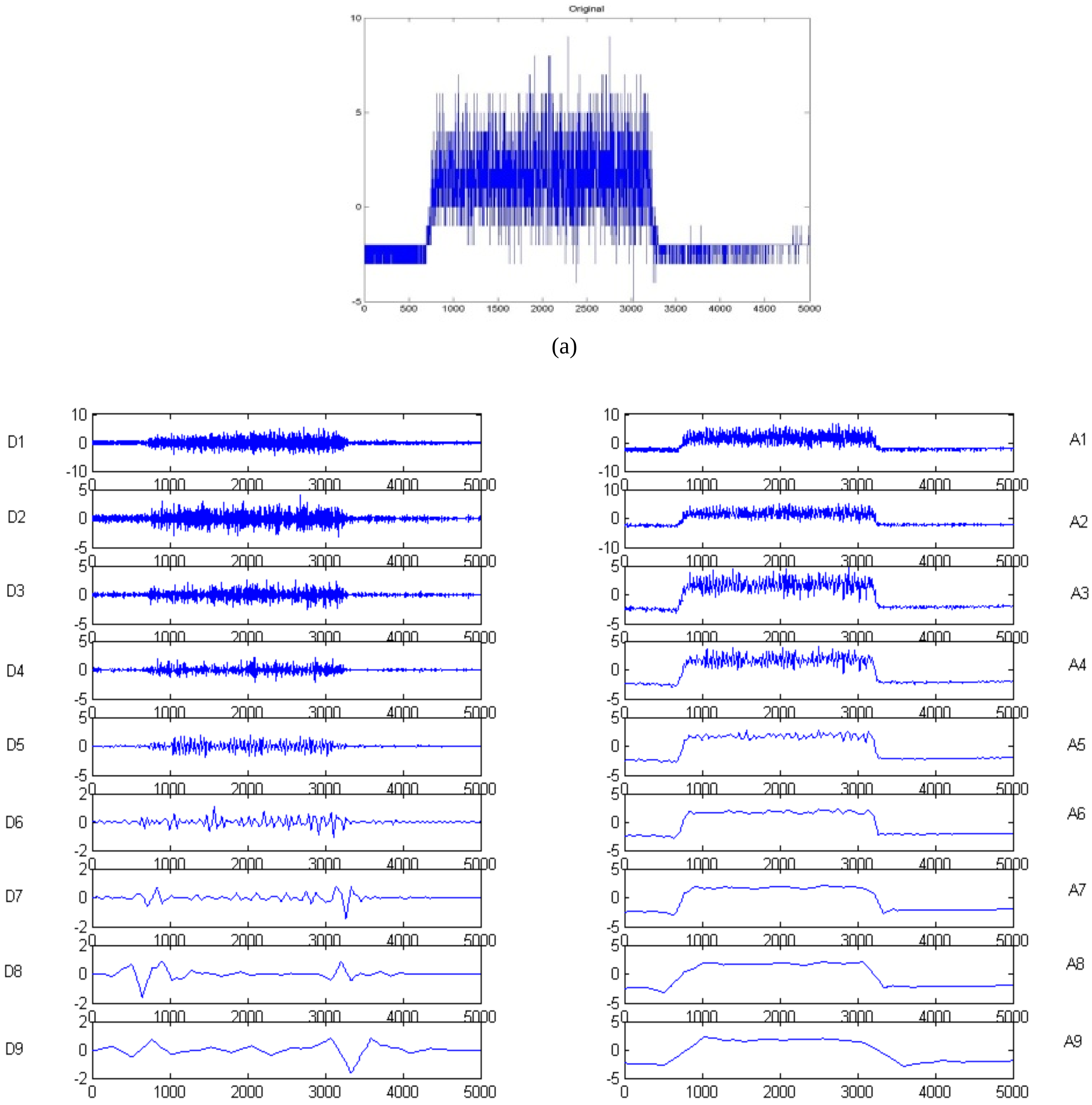


Fig. 7. Structure of the signal decomposition of cutting force

Fig 8 shows an example of signal decomposition of a cutting force; which is the test n° 17 (Parameters of cut: **Vw:** 1 m/mn; **Vd:** 2 m/s. a**:** 20µm **Np:** 10).



(a)

(b)

(c)

Fig 8. Test N°17

(a) The cutting force signal (Parameters of cut: Vw: 1 m/mn; Vd: 2 m/s; a: 20µm; Np:10)
(b) The coefficients of details at different levels
(c) The coefficients of approximations at different levels.

Let’s note that the approximations indicate the points of input/output of the tool in the workpiece, they correspond to the low frequencies of the components signal of grinding force. The variation of the signals due to the difference between the surfaces quality, if it is detectable by the wavelet decomposition can appear only on the coefficients of details. Indeed, the variation of the coefficients of approximation seems to be controlled only by the signal amplitude. Thereafter, we will carry out a statistical analysis of the coefficients of details in order to establish a correlation, if there exists, between the statistical parameters and the micro geometrical characteristics of rectified surfaces (Rt and Ra). “Rt” characterizes the most important difference in level between the highest summit of a peak and the lowest of a hollow realized by the grinding stone in contact with surface and “Ra” represents the arithmetic mean of the absolute values of the differences between the peaks and the hollows. For that, these measurements will be recorded independently of the signals of cutting force with a roughmeter of stylet Hommel Tester T1000. The results are represented in table 2.

Table 2. The calculation of the statistical parameters and the roughness parameters

#: Cut grains of the grinding stone; **Vw:** Speed in advance [m/mn]; **Vd:** Speed of raising [m/s] **a:** Depth of cut [µm]; **Np:** Numbers of cut; **Rt:** Roughness [µm]; **S:** standard deviation of the coefficients of details

Test N°	**Factors**					**Roughness parameters**		**Statistical parameters**				
	#	**Vw**	**Vd**	**a**	**Np**	Rt [µm]	Ra [µm]	$\overline{cD}_j$	S	Median AD	Average AD	
14	60	1	2	5	20	2,43	0,3	0,3651	1,735	0,6841	1,132	Interval I
13	60	1	2	5	10	2,20	0,6	0,2197	2,186	0,7932	1,458	
1	60	1	8,2	5	10	3,10	0,43	0,0194	2,542	0,5146	1,492	Interval II
2	60	1	8,2	5	20	3,30	0,5	- 0,9244	2,773	0,6866	1,926	
7	60	1	4	5	10	3,10	0,9	- 0,1735	2,885	1,075	1,75	
8	60	1	4	5	20	3,30	0,5	- 0,3276	3,061	0,536	1,743	
9	60	1	4	10	10	3,40	0,4	0,0675	3,962	1,276	2,428	
10	60	1	4	10	20	4,00	0,4	- 0,0524	4,054	0,7797	2,521	Interval III
16	60	1	2	10	20	4,09	0,4	1,823	4,197	0,8873	2,878	
3	60	1	8,2	10	10	4,63	0,7	1,481	4,258	1,912	3,026	
4	60	1	8,2	10	20	4,83	0,8	- 0,147	4,646	1,902	2,996	
15	60	1	2	10	10	3,11	0,33	- 2,294	5,457	1,053	3,945	
5	60	1	8,2	20	10	4,73	0,87	2,603	7,523	2,679	5,656	
17	60	1	2	20	10	4,26	0,5	- 1,34	7,964	2,61	5,019	
18	60	1	2	20	20	4,30	0,63	- 2,684	8,223	3,208	6,166	
11	60	1	4	20	10	4,26	0,5	- 0,8826	9,093	2,769	5,368	
6	60	1	8,2	20	20	6,36	0,63	- 1,89	9,121	2,164	6,397	
12	60	1	4	20	20	4,30	0,53	2,477	10,06	3,127	7,283	
32	60	8	2	5	20	4,32	0,57	- 3,131	10,08	0,5962	7,127	
50	60	14	2	5	20	4,64	0,73	0,3138	11,09	0,8478	5,676	
19	60	8	8,2	5	10	5,53	1,17	1,994	11,34	0,3489	6,311	
31	60	8	2	5	10	4,45	0,5	6,076	12,54	3,12	9,337	
49	60	14	2	5	10	4,55	0,7	- 0,2802	14,09	0,4159	7,16	
25	60	8	4	5	10	4,63	0,67	5,886	15,09	3,736	9,621	
38	60	14	8,2	5	20	9,64	1,73	- 7,002	19,64	0,7587	13,77	
20	60	8	8,2	5	20	9,00	1,37	- 4,044	19,72	0,7347	13,36	
43	60	14	4	5	10	5,40	0,9	- 4,783	20,46	0,6332	11,4	Interval IV
33	60	8	2	10	10	5,18	0,73	9,96	21,19	2,019	13,5	
27	60	8	4	10	10	5,50	0,8	10,09	22,22	5,603	16,22	
26	60	8	4	5	20	5,33	0,7	- 1,172	23,04	0,858	12,53	
44	60	14	4	5	20	5,56	0,97	2,482	25,44	0,8318	13,48	
28	60	8	4	10	20	5,86	1	6,818	29,51	0,6258	16,14	
52	60	14	2	10	20	6,40	0,97	3,75	30,59	0,4937	16,59	Interval V
34	60	8	2	10	20	6,38	0,77	- 6,806	30,77	0,847	21,48	
21	60	8	8,2	10	10	11,12	1,4	- 7,748	31,74	1,22	22,22	
30	60	8	4	20	20	6,70	1,57	4,592	32,88	2,359	18,47	
36	60	8	2	20	20	6,86	1,67	13,2	33,85	1,963	22,79	
22	60	8	8,2	10	20	11,60	1,87	- 7,526	34,95	1,005	23,95	
39	60	14	8,2	10	10	12,90	3	- 2,842	35,57	1,617	18,28	
45	60	14	4	10	10	6,46	1,23	- 14,68	37,92	1,036	26,04	
29	60	8	4	20	10	6,73	1,33	17,24	38,57	6,046	25,16	
35	60	8	2	20	10	6,26	1,17	16,65	39,02	8,625	25,75	
37	60	14	8,2	5	10	8,54	1,83	7,699	39,61	0,8629	21,71	
51	60	14	2	10	10	6,96	0,8	3,627	39,96	1,153	21,27	
24	60	8	8,2	20	20	9,60	2,9	- 0,9332	42,81	2,277	24,54	
23	60	8	8,2	20	10	8,12	2	1,206	53,29	1,553	27,6	Interval VI
40	60	14	8,2	10	20	13,20	3,07	6,14	56,26	1,164	29,33	
46	60	14	4	10	20	8,30	1,4	3,187	57,1	1,487	29,29	
54	60	14	2	20	20	8,53	1,27	- 19,79	58,12	1,226	39,78	
47	60	14	4	20	10	10,91	1,4	- 27,33	76,26	2,131	54,36	
53	60	14	2	20	10	10,41	0,93	- 17,02	83,66	2,316	45,56	
48	60	14	4	20	20	11,65	1,47	4,766	84,93	1,871	43,39	
41	60	14	8,2	20	10	15,80	3,37	22,05	122,6	0,746	67,3	
42	60	14	8,2	20	20	17,30	3,47	18,86	124,4	1,29	67,92	

The curves in fig 9 represent the roughness parameters Ra and Rt according to the number of the grinding tests.

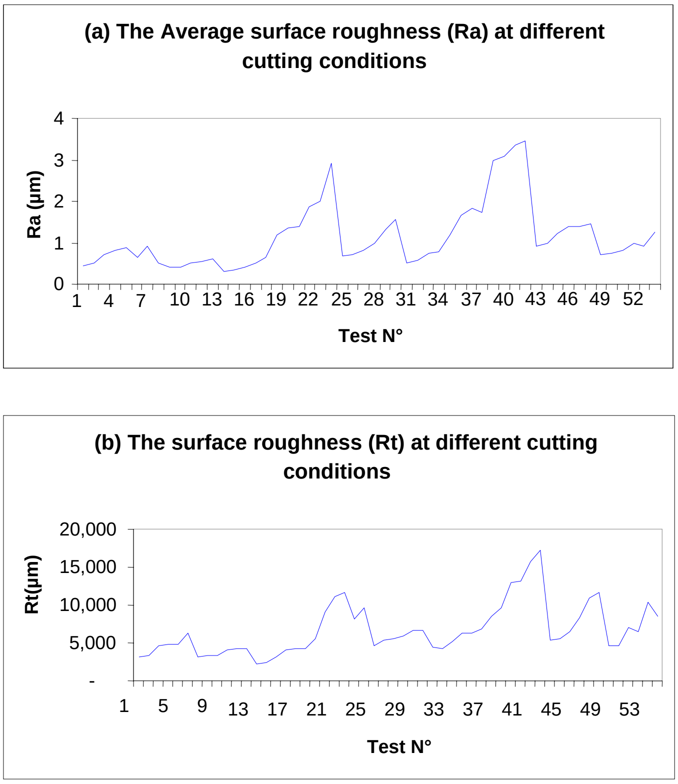
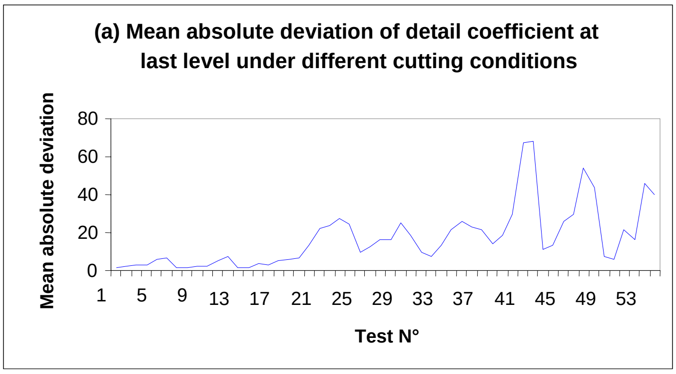
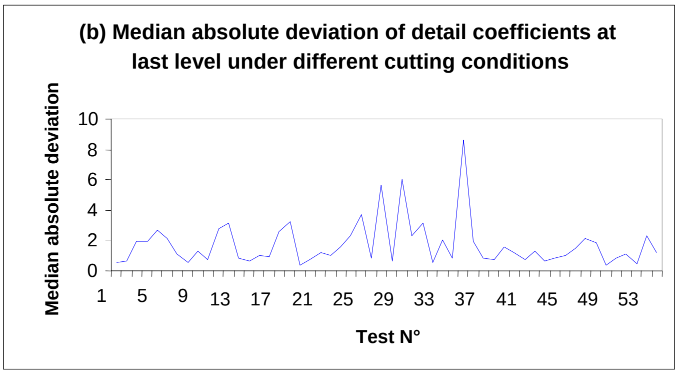


Fig. 9. Representation of the roughness parameters

After the calculation of the different statistical parameters, different curves representing these indices are plotted for the various tests (fig 10).





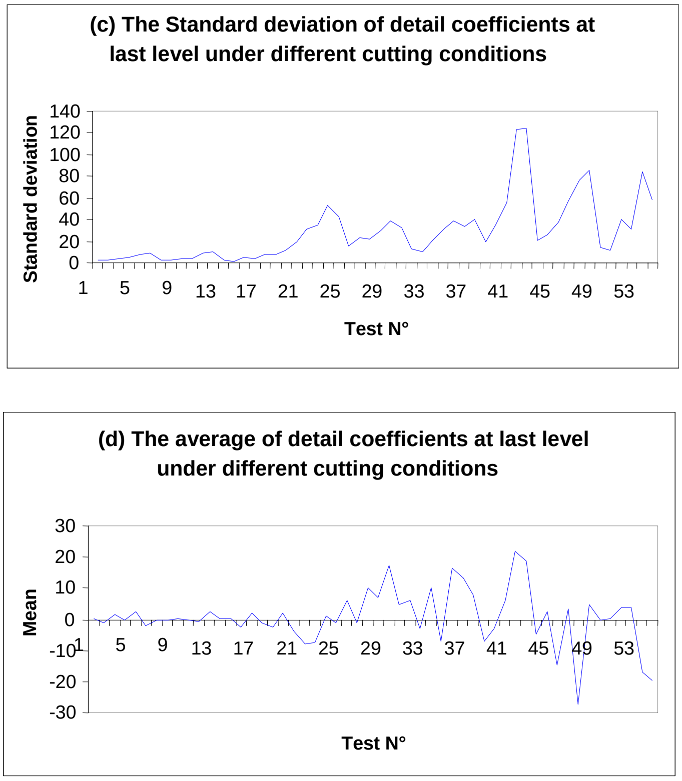


Fig. 10. Representation of the statistical parameters

The comparison between the statistical parameters and the roughness parameters, given by fig *9* and *10*, shows that the curves of the standard deviation and the average deviation (Fig 10.a and 10.c) are sensitive to the variations of roughness surface Rt (Fig 9.b) for the majority of the tests carried out. Indeed, an increase in the surface roughness is followed by an increase in the standard deviation and vice versa in the case of the reduction. The standard deviation shows a sensitivity to the variations of the grinding force signal which are due to the variations of the surface roughness Rt. The results of these experiments are represented in table 3. These results are validated for 70% of the tests on workpiece under various grinding conditions (table 2).

Table 3. Variation of the standard deviation of the coefficients of details of cutting force signal compared to measurements of the surface roughness Rt

Intervals	**Standard deviation “S”**	**Rt (µm)**
I	1.5 → 2.5	2 → 3
II	2.5 → 4	3 → 4
III	4 → 20	4 → 5
IV	20 → 30	5 → 6
V	30 → 40	6 → 7
VI	50 → 60	8 → 9

5. CONCLUSION

The work presented in this paper proposes an indirect predictive monitoring method to predict in real time the surfaces roughness (Rt) of the rectified parts. As it is difficult to measure this surface parameter in real time, it is often given in an indirect way through the measurement of another parameter more easily measurable. In the literature, we found several techniques in the phase of the follow-up of system evolution like the use of sound emission, vibration signals or electric output consumed by the process. However, these techniques do not give access to necessary information on the value of the surface roughness. For this reason, a methodology is developed which is based on the analysis of the cutting force signals by the wavelet transform and the establishment of correlation between roughness (Rt) and the coefficients of details. The follow-up of system evolution obtained by the exploitation of the wavelet transform made it possible to achieve a double target: the follow-up of the deterioration of the quality of the rectified piece, and the evaluation of the cutting tool state during the grinding process.

The most outstanding results of this study can be summarized as follows:

✓ The Daubechies wavelets of order 3 are largely necessary to carry out the multi level analysis of the cutting force signals in grinding.

✓ The variation of the signals caused by the micro geometrical state of rectified surfaces appears in the coefficients of details.

✓ The statistical indices like the standard deviation and the average deviation vary in the same way that surface roughness (Rt)

✓ The roughness values (Rt) predicted from the cutting force signals correspond in 70% of the cases to the measured values on the machined piece under the tests conditions of the experimental design.

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