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# MILLING CUTTING TOOL DIAGNOSIS USING COMPARISONS OF THE EXCITATION IDENTIFIED BY CEPSTRAL TECHNIQUES

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**Abstract**

This paper investigates the diagnosis of cutting tools in a milling operation using vibration signals and proposes a signal processing algorithm to achieve that. In the proposed algorithm, the impulse response of the measured vibration signal is firstly identified using the random decrement technique. This is then converted to a cepstrum and subtracted from the measured signal in the quefrency domain using the additive properties of cepstra. The residual signal representing the forcing function is then transformed back into the time domain using the inverse cepstrum. Finally the power spectral density is estimated, and a comparison is made between the different states of the cutting tool. For a good estimation of the force, four measurement points are used, and the identified excitation sources are then averaged. By comparing the spectra of the forcing functions, the efficiency of the method is demonstrated, and the faulty case is clearly distinguished from the fault-free case. This was not the case with the original response signals.

*Keywords:* Random decrement, complex cepstrum, blind identification, diagnosis, milling cutting tools.

## 1 Introduction

The identification of the state of a cutting tool is important in any metal cutting process; as additional cost - in terms of scrapped components, machine tool breakage and unscheduled downtime - occurs as a result of tool defects. Tool wear and breakage are the most encountered defects in the machining process [1]. Several factors such as cutting conditions, workpiece surface and tool geometry make the condition monitoring of the tool complex; especially when developing an effective system to monitor the early stages of the fault in the tool-tip. Several parameters have been proposed for the condition monitoring. Among these are the cutting forces, vibration signatures, temperature and acoustic emission. For each of these parameters, several features have been tried such as the power spectral density (PSD), kurtosis, etc.

Acoustic emission proved efficient for detecting the tool breakage but less suitable for monitoring the tool wear [2]. The measurement of cutting forces requires special mounting fixtures [2]. The vibration signal has been proved effective in the diagnosis of tool wear monitoring and is easy to acquire [2, 3]. However, the different transmission paths distort the signals at different measurement points.
The identification of the transmission path/excitation is one of the methods that have been used for the diagnosis of the cutting process. In [4] a blind identification method based on the bicepstrum was used to estimate the characteristics of the precision turning process. In this current work a vibration signal approach is proposed to identify the excitation source and to monitor the tool state.
The paper is organized as follows. In section 2, we introduce the blind identification method and explain its essentials. In section 3, the experimental measurements and their analysis are discussed. Finally, the conclusion and perspectives are given in section 4.

## 2. Theoretical background:

### 2.1 Random Decrement technique:

The Random-Decrement (RD) is a signal processing technique which transforms the response of a resonant system to random excitation, into its impulse response. It was developed by H.A Coles at NASA during the late 60s and early 70s [5] in order to detect space structure damage from the measured response. Since then, it has been applied to a wide variety of structures subjected to un-measurable ambient excitations, to extract the modal parameters and eventually to detect failures.

The technique was later given a mathematical basis. Let *X(t)* be a stochastic process, the RD function is defined as the mean value of a stochastic process on condition, T, of the process itself |6]:

$$D_{XX}(\mathrm{t}) = E\left[X(t+\mathrm{t})\middle|T_{X(t)}\right] \tag{1}$$

The condition T is the triggering condition.
In order to estimate the conditional mean value correctly from a single observation it is necessary to assume that the stochastic process is not only stationary but also ergodic. In this case the RD function can be estimated as the empirical conditional mean value from a single realization:

$$\hat{D}_{XX}(\mathrm{t}) = \frac{1}{N}\sum_{i=1}^{N} x(t_i+\mathrm{t})\middle|T_{x(t_i)} \tag{2}$$

Where *N* is the number of points in the process which fulfils the triggering condition and *x(t)* is a realisation of *X(t).* The triggering condition used in this work is $T_{x(t_{i+1})} = \{x(t_{i+1}) > 0 > x(t_i)\}$, ie a positive going zero crossing.

In damage failure detection the basic idea is often that an incipient failure will change the stiffness and the damping characteristics of the structure. In this case, the tool tip damage has little effect on the system properties (except possibly damping) but primarily changes the forcing function. The RD functions can be used to remove the different transfer functions to obtain several estimates of the single forcing function which can be averaged.

### 2.2 Complex Cepstrum:

Cepstral analysis is a technique that transforms a convolution to an additive relationship [7]. The complex cepstrum is defined by:

$$c_x(\mathrm{t}) = FFT^{-1}[\log(X(f))] \tag{3}$$

Where $X(f)$ is the Fourier transform of *x (t)* and $FFT^{-1}$ is the inverse Fast Fourier Transform [8].
We apply (3) to the relationship between the input *e*(*t*) (excitation source) and output *x*(*t*) for a Single input Multiple output (SIMO) system:

$$x(t) = e(t) * h(t) \tag{4}$$

Where *h*(*t*) is the impulse response of the system for that response point.

The complex cepstrum of (4) transforms the convolution in the time domain into an addition in the quefrency domain (also having dimensions of time) [7] as:

$$c_x(\mathrm{t}) = c_e(\mathrm{t}) + c_h(\mathrm{t}) \tag{5}$$

As seen from (5) the source and path phenomena are additive. The excitation force can be recovered very easily if the system impulse response estimates are available. The cepstrum has proved very useful in condition monitoring and fault diagnostics of mechanical systems, especially in the case of operating machines where periodic excitation sources exist, such as gear meshing forces, and milling cutting forces Two applications are widely used in condition monitoring and fault diagnostics: extraction of vibration features corresponding to given mechanical faults, and recovery of the vibration sources and transmission paths [8].

### 2.3 The schematic presentation of the algorithm:

Figure 1 illustrates the flow chart of the blind identification process that is used in this work. The impulse responses $\hat{h}_i(t)$ of the measured vibration signals $x_i(t)$ (acceleration) are firstly identified using the random decrement technique (the length of the sequence is padded with zeros to have the same size as the original measured signal *x(t)*). This impulse response is then transformed into the quefrency domain $c_{\hat{h}_i}(\mathrm{t})$, as is the measured signal $c_x(\mathrm{t})$, by means of the complex cepstrum. In this domain the system properties and the excitation are additive and can then be separated by a simple subtraction. The transfer function is subtracted from the signal and the remainder $c_{\hat{e}_i}(\mathrm{t})$ is transformed back to the temporal domain $\hat{e}_i(t)$ by the inverse complex cepstrum. The process presented in the figure 1 is calculated for each measurement point and the excitation forces obtained are then averaged to obtain an improved estimation of the excitation force.

Finally, by using PSD comparison the tool cutting state can be diagnosed.

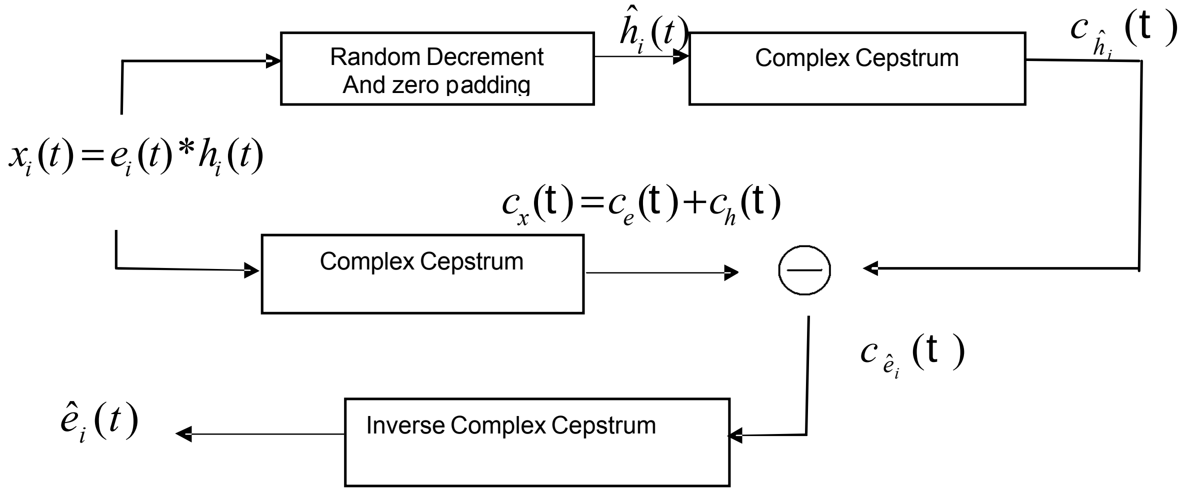


Figure 1 Schematic presentation of the identification algorithm.

## 3 Experimental results:

### 3.1 Test rig:

A test rig to generate cutting data from a milling operation was prepared. Four accelerometers (gain 100mv/g), were placed in three mutually perpendicular directions [x direction, y workpiece, -y, z direction as shown in figure 2]. An optical encoder to enable the angular sampling was installed in the spindle, (figure 2). It delivers a position information (squared signal at frequency 2500*$f_r$, where $f_r$ is the rotational speed) which is used as a clock for the data acquisition card. Therefore, signals were sampled at constant angle intervals. Note that while it was important to have a fixed number of samples per rotation of the cutting tool, the speed was very constant, so the rotation axis still corresponded to a time axis and preserved natural frequencies.

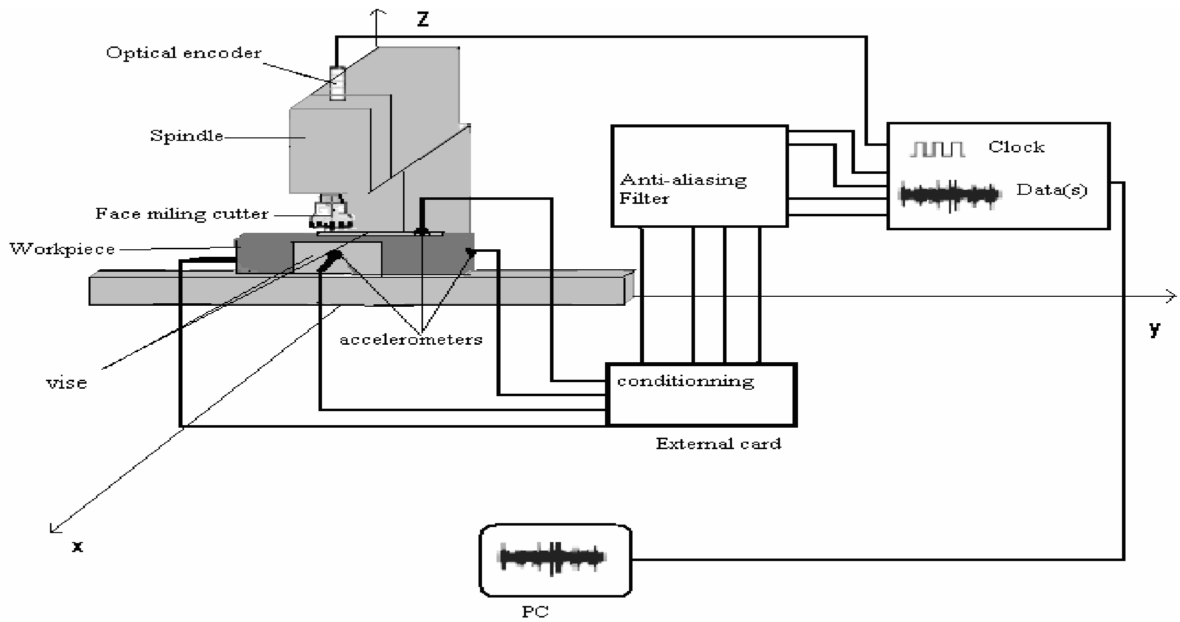


Figure 2 Schematic presentation of the experimental setup.

Experiments with the milling cutting tool were performed for one minute of milling. The face milling cutter had 5 unequally spaced teeth. The cutting parameters and the operating conditions were kept constant during the experiment (see table 1).

In the experimental analysis, we have considered three tool cutting states: without fault, with two worn teeth (0.2mm) and with a broken tooth.

Table 1 Cutting conditions and angular sampling parameters.

| | |
|---|---|
| Material of the specimen | steel |
| Rotation speed | 650 rpm |
| Feed rate | 220 mm/min |
| Milling cutter diameter | 100mm |
| Number of teeth | 5 |
| Cutting depth | 0.7mm |
| Optical encoder resolution | 2500 points per revolution |
| Number of recorded cycles | 500 |
| Number of samples | 1250000 samples |
| Averaged sampling rate | 27 kHz |
| Anti-aliasing filter | 9 kHz |

### 3.2 Analysis of the results:

Figure 3 presents three cycles of the signal from the four sensors in the fault free case. It shows the repetition of the peaks that correspond to each tooth when it enters in the workpiece. This repetition shows the cyclostationary nature of the milling vibration signal taken under angular sampling. It shows that the magnitude of each sensor signal is different from the others. The signal number 2 has a large magnitude because the sensor is arranged in the cutting force direction.

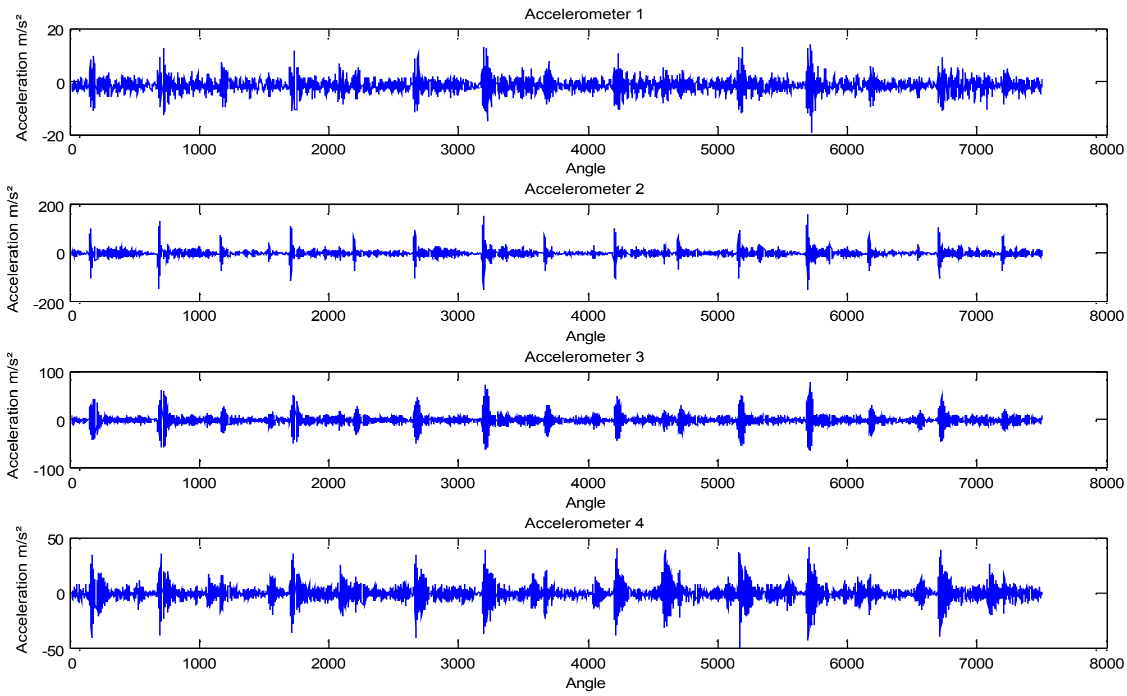


Figure 3 Typical milling signals for different sensors

Figure 4 presents a segment of the excitation signal identified from sensor 4 by the process presented in figure 1, the arrows indicate the excitation impulsion, it is seen that it consists of an impulse that represents the force. This is a sample of the identification procedure applied on the entire signal.
The objective of this procedure, as indicated in the introduction, is the diagnosis of different states of the cutting tool. To achieve this, all identified excitation forces are averaged and then the PSD is applied. The identified forces were much more similar than the responses at each point.

Figure 5 shows the PSD computed for the measured response signals averaged for all the sensors. Here the fault-free case and the case with a broken tooth are presented. As can be seen in this figure, there are many peaks which correspond to the system resonances. For these two cases presented it

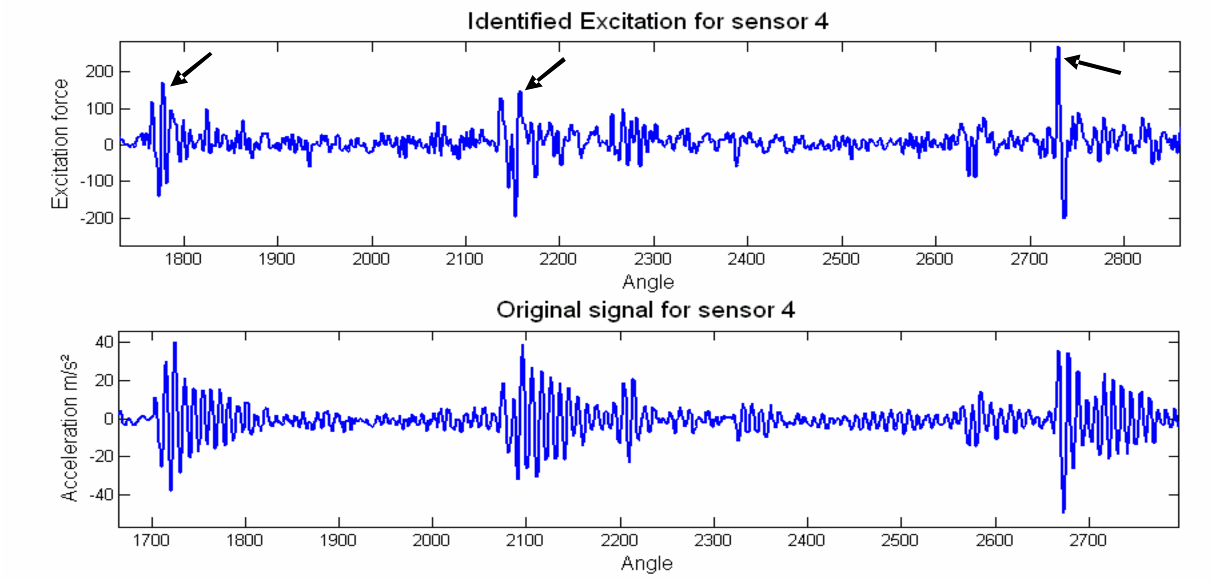


Figure 4 Typical Identified signal from sensor 4, top the identified signal, down the original signal

is clear that there is no significant difference detected from the response signals. The conclusion is that the direct application of PSD analysis to the averaged measurements does not give any information about the fault because of the distortion given by the different transfer paths.


Figure 5 PSD of the averaged signal for different sensors, for the fault-free case and a broken tooth

Figure 6 shows the power spectral density computed for the averaged identified excitation force. Note that the identified force spectra have a flattened characteristic that is typical of a white excitation because of the removal of the transfer function information. There are some peaks in the low frequency region, but the rest is quite uniform.

Also it is clear that there is a big difference between two of the cases in the frequency range [2-4 kHz] which corresponds to the main system resonances in Fig. 5. This difference has a maximum in the range [2000-2500Hz], for a broken tooth of more than 10dB, which is very significant. For two worn teeth, the maximum difference is 6dB. The conclusion is that this method enables making a distinction between faulty cases and the fault-free case. In [9] higher order statistics are used for the diagnosis, but the inconvenience with that method is the large computational burden. The current method does not need to employ higher order statistics and is therefore of considerable interest in condition monitoring.

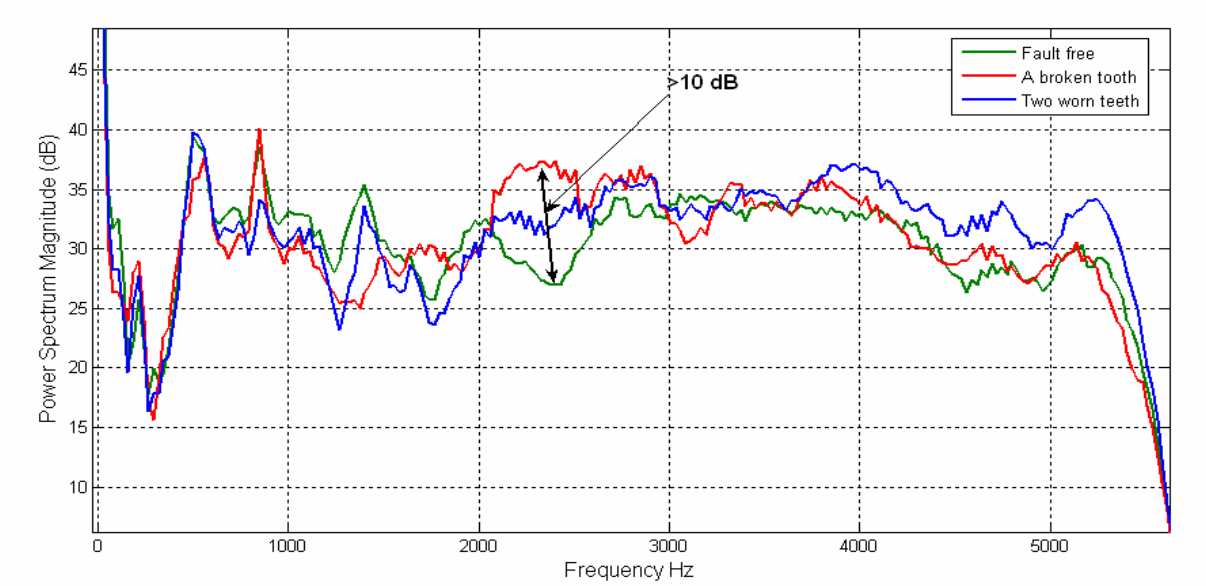


Figure 6 PSD of the average identified signal for different sensors, for the free fault, two worn teeth and a broken tooth

## 4 Conclusion and perspective:

In this work a blind identification method is proposed, it consists of the use of the random decrement for impulse response estimation and the cepstrum to separate the common excitation force from these different impulse responses. As seen by the results of the application to milling cutter signals, an ability is shown to distinguish between the faulty cases and the fault-free case. once the differences in the zone dominated by the system responses are removed. It has been seen that for the case of a broken tooth the difference in dB is more than 10dB, whereas in the case of two worn teeth the difference of 6 dB is just significant. On the other hand it is seen that there is no significant difference when the measurement signals are directly used. Therefore, this method of identification can be used for the diagnosis of milling cutting tools.

The perspective also exists to use other more advanced techniques that make use of the cyclostationary properties such as spectral correlation, and synchronous average, since the signal is sampled in the angular domain with a fixed number of samples per cutting cycle.

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