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Multi sensor signal processing for catastrophic tool failure detection in turning

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Abstract

This paper presents a methodology aimed at the identification of a catastrophic tool failure (CTF) in turning processes based on multiple sensor monitoring. Experimental turning tests were carried out under various cutting conditions (cutting speed, feed, depth of cut) using a multi-sensor monitoring system consisting of a triaxial force sensor to acquire the three components of the cutting force and an acoustic emission sensor. Signals analysis, interpretation and processing was performed on the multi-sensor signals acquired during the turning process and relevant statistical features were extracted and used to develop a methodology for the automatic CTF detection during turning.

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Keywords: Catastrophic tool failure; Turning; Sensor monitoring; Signal processing; Feature extraction

1. Introduction

In automated machining processes, tool condition monitoring can profitably contribute to the decrease of production costs by reducing downtime and unnecessary tool changes, and represents a valuable method for improving the product quality by eliminating chatter and poor surface finish [1]. In the past years, a number of research studies on have been conducted this topic, however further research is needed to develop a reliable and cost-effective tool condition monitoring system for applications on the shop floor, especially when dealing with variable cutting conditions [2].

Most of the research work conducted so far is based on an approach consisting of three steps. The first step involves sensing of monitoring signals, such as force, vibration (mostly acceleration), sound or acoustic emissions, temperature or heat, and power (motor current). The second step is signal processing to extract a set of monitoring indices, also called features or attributes. The last step is classification, in which the features are used to classify the current tool condition based on the existing knowledge on pre-defined tool conditions. Owing to the complexity of machining processes, there may not be a single sensor signal or a monitoring index that can uniquely identify the tool conditions [3]. Tool conditions, such as tool breakage and tool wear, can be manifested in various forms. In addition, combined tool failures may happen, such as cases where tool breakage and chatter occur at the same time [4].

Tool failure generically indicates the condition in which the tool no longer performs the desired function. Specifically, a catastrophic tool failure (CTF) may occur in different ways, for example through brittle failure of the cutting edge, such as chipping or breaking [5]. CTF might cause substantial damages to the workpiece and/or the machine tool. Therefore, the ability to detect the occurrence of a catastrophic tool failure during machining is essential to reduce workpiece scrappages and machine downtime and may have a positive effect on productivity, profitability and environmental impact.

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With this aim, a new methodological approach for the detection of CTF in turning is proposed in this paper. The methodology is based the employment of a multiple sensor monitoring system consisting of a triaxial force sensor (to acquire the three components of the cutting force) and an acoustic emission sensor. The sensor signals of different nature were acquired during experimental turning tests carried out under various cutting conditions (cutting speed, feed rate, depth of cut). Signals analysis, interpretation and processing was performed on the acquired signals and relevant statistical features were extracted and used to develop a methodology for CTF detection. An algorithm was developed and implemented in LabVIEW to automatically detect the occurrence of a CTF during turning based on the values of the selected statistical features in all the acquired signals.

The research activity presented in this paper has been developed within the framework of the EC FP7 Project "Realism - Real Time In Situ Monitoring of Tool Wear in Precision Engineering Applications", in collaboration between the University of Naples and the Warsaw University of Technology, that provided the sensor monitoring signals used to construct the CTF methodology.

2. Sensor monitoring of turning processes for CTF detection

In the literature, a few methodologies to detect the occurrence of a catastrophic tool failure during turning processes have been proposed [6-9]. These methodologies are based on the employment of multiple sensor monitoring systems, mainly dedicated to the acquisition of cutting force and vibration signals during the process. According to Kim and Choi [6] and Wang and Gao [5], continuous signal collection of cutting force, acceleration and displacement at specific cutting conditions should be carried out. In their methodologies, the features obtained from signal processing are used for the calculation of thresholds and values of relevant parameters (normalized cutting force, etc.) to be compared with thresholds. If the value of the parameter is under the threshold, then the signal collection proceeds with new updated thresholds, otherwise a control action should be performed (e.g. the machine is stopped) [6].

In this framework, the objective of this paper is to develop a methodology for the on-line detection of a catastrophic tool failure based on the acquisition of relevant signals during the turning process. In order to develop such methodology, experimental turning tests were carried out at the Warsaw University of Technology. For these tests, a multiple sensor monitoring system made of two different sensors was installed on the machine tool to monitor the process.

2.1. Experimental set-up

In order to develop an automatic procedure for CTF detection during turning processes, an experimental testing campaign was performed to acquire relevant sensor signals during turning processes. In order to acquire a number of sensor signals corresponding to different cutting conditions, several turning tests were performed on a workpiece made of 42CrMo4 steel. The machine tool employed for the tests was a TKX 50 N turning centre.

Three different cutting conditions (called Type 1, Type 2, Type 3) were adopted: the values of the turning parameters, i.e. cutting speed, *v*, feed, *f*, and depth of cut, *d*, are reported in Table 1. Under each cutting condition, several tests were carried out until a CTF occurrence was verified. As regards the type of movement of the tool during the turning process, a longitudinal cutting was performed.

2.2. Multiple sensor monitoring system

With the aim to acquire relevant signals during the experimental turning tests, a multiple sensor monitoring system was employed. Sensors for process monitoring must meet the following requirements: measurement as close to the machining point as possible; no reduction in the static and dynamic stiffness of the machine tool; no restriction of working space and cutting parameters; wear- and maintenance-free, easily changed, low costs; resistant to dirt, chips and mechanical, electromagnetic and thermal influences, etc. The combination of different, inexpensive sensors today is ever increasing to overcome shortages of single sensor devices [10-16]. There are two possible ways to achieve a multi sensor approach: the first is obtained using one sensor that allows measurement of different variables, in the other different sensors are attached to the machine tool to measure different variables [10]. In this research activity, two different sensors have been employed during the turning tests: a cutting force sensor to measure the three orthogonal force components F_x, F_y and F_z, and another sensor to measure the acoustic emission AE during the machining process. The force sensor was mounted on the clamps. The advantage of this multiple sensor system is the possibility to combine the information related to different process variables, the cutting force and the acoustic emission. With these sensors a more reliable tool breakage detection becomes possible. Table 2 shows the cutting force and the acoustic emission sensors employed for the tests (Fig. 1 a-b) as well as the adopted sampling rate.

Table 1. Turning parameters: cutting speed, *v*, feed, *f*, depth of cut, *d*

Signals	v [m/min]	f [mm/rev]	d [mm]
Type 1	250	0,15	1
Type 2	580	0,1	1
Type 3	335	0,15	2-1-2

Table 2. Sensors and sampling frequency employed in the experimental tests

Signals	Sensor for cutting force	Sensor for AE_{RMS}	f_s (kHz)
Type 1 Type 2 Type 3	Kistler 9017B	Kistler 8152B	10

(a) (b)

Fig 1. Sensors used for monitoring: (a) Kistler 9017B triaxial force sensor (b) Kistler 8152B acoustic emission sensor

3. Signal processing and feature extraction for CTF detection

For each of three cutting conditions adopted in the experimental turning tests, two types of signals were employed for the analysis: one with CTF occurrence and the other without CTF occurrence. These signals, acquired during the turning tests by means of the described sensor monitoring system, consisted of the three components of the cutting force (F_x, F_y and F_z) and the root-mean-square, RMS, of the acoustic emission signal (AE_{RMS}) acquired with a sampling rate of 10 kHz.

The methodology used to detect the CTF occurrence was based on signal processing and feature extraction. The first step of the analysis consisted in plotting the cutting force signals and the acoustic emission RMS signal vs time in order to examine the behaviour of the signals in case of CTF occurrence. The visual examination resulted relatively simple because the corresponding signals were characterized by a large variation of the trend in case of CTF occurrence. In particular, this variation was more evident in the cutting force components signals rather than in the acoustic emission RMS signals. This may be due to the critical influence of the noise of the machining process on the acoustic emission signal. This behaviour can be observed in Figs. 2-3, showing the F_x signal and the AE_{RMS} signal referring to a case of CTF occurrence.

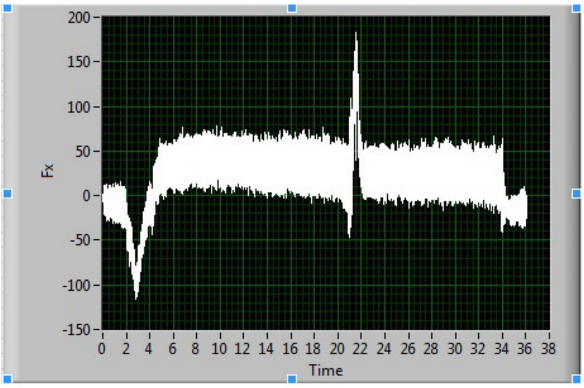


Fig 2. F_x signal vs time (s). The signal refers to a case of CTF occurrence.

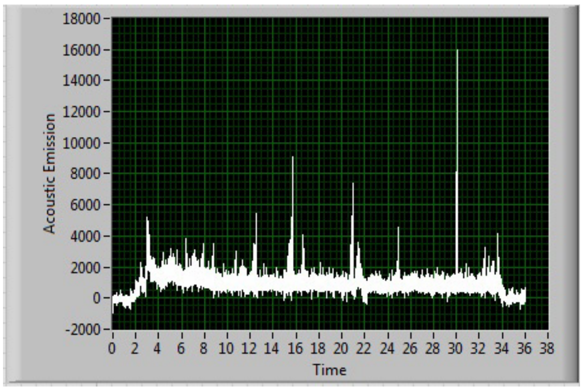


Fig 3. Acoustic Emission RMS signal vs time (s). The signal refers to a case of CTF occurrence.

As it can be observed in Figs. 2-3, each signal is made up of two parts: the first part, generally lasting few seconds, refers to the instants before the starting of the machining, while the second part is related to the real machining process. Since the first part of the signal is useless for CTF detection, a methodology was developed in order to detect the beginning of machining and therefore analyze only the second part of the signal to detect the CTF occurrence.

To delete the useless part of the signals, an algorithm was created using the software LabVIEW and analyzing only the data referred to the F_x component of the cutting force. The algorithm was able to detect the time instant in which the machining process starts based on a statistical approach. Statistical features (signal mean and variance) were extracted from the signals over consecutive signal portions made of a fixed number of samplings (100 samplings). The algorithm starts by considering the mobile mean with 100 samplings and identifies the value of the mean that it is greater than zero. From this value, a comparison is carried out between each element of the recorded signals and the subsequent ten elements. The comparison is done by searching when this difference is greater than a threshold equal to 8; once this value is identified, the algorithm doesn’t stop but continues until the last value for which this condition is true is obtained. This instant is identified as the beginning of the machining process and it is used to cut the relevant portion of the signal.

3.1. Catastrophic tool failure detection based on a statistical approach

Once the useful portion of the signal corresponding to the machining process was extracted, a methodology for CTF detection was implemented by extracting statistical features (signal mean and variance) from the signals. This approach is based on calculations performed over signal sub-portions made of a fixed number of samplings. As explained later, the number of samplings was progressively reduced from 500 samplings down to 100 samplings during the optimization of the methodology in order to enable the system to respond as quickly as possible during the turning process.

To automatically detect the CTF occurrence using the sensor signals acquired during the machining process, an algorithm was developed using the National Instrument LabVIEW visual programming language. Two methodologies were applied for the analysis of the cutting force signals and for the acoustic emission signals. Both methodologies start by analyzing the signals from the time instant identified as the beginning of the machining. As regards the procedure for processing and feature extraction of the cutting force signals, for each cutting force component, the variance of the recorded signal values was analyzed considering signal sub-portions of n samplings. The variance calculated on each signal sub-portion was compared with the calculated variance of the consecutive signal sub-portion. If the ratio between the variance values was higher than a threshold, a CTF occurrence was detected. The value of the threshold was different for each component (F_x, F_y, F_z) of the cutting force and the number of samplings taken into consideration. The number of samplings, n, was progressively reduced during the analysis from the starting value of 500 samplings to a minimum value of 100 samplings in order to provide a quicker response to the occurrence of the CTF.

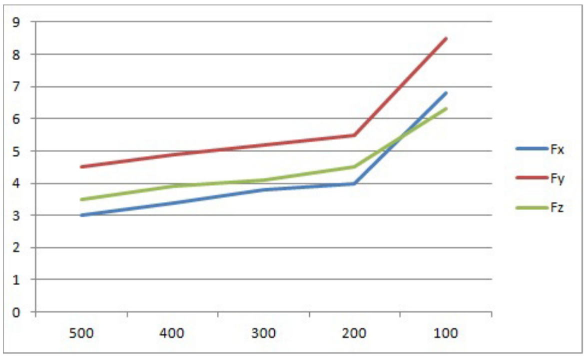


Fig 4. Trend of the threshold value as a function of the number of samplings for each of the cutting force components

The values of the threshold were adjusted based on the number of samplings of each signal sub-portions. Figure 4 shows the threshold values as a function of the signal sub-portion length, from 500 samplings down to 100 samplings.

Using the data in Figure 4, it is possible to observe the trend of the threshold value for each component of the cutting force as well as the threshold value as a function of the number of samplings employed for the statistical feature extraction. Going from 500 to 100 samplings, the slope of the threshold remains almost constant, while from 200 to 100 samplings, a significant adjustment of the threshold was necessary to correctly identify the CTF occurrence.

On the other hand, as regards the processing of the acoustic emission signal, two different methodologies were applied: one procedure is based on the approach reported by Jemielniak et al. in previous studies on CTF detection [7-9] and the other procedure is based on a methodology similar to the one previously illustrated for the cutting force signals.

In the first methodology, the AE_{RMS} signals were analysed considering 500 values samplings. For each sub-portion of 500 samplings, the kurtosis was calculated. The aim was to identify the CTF by analysing the trend of the change of the acoustic emission kurtosis. Therefore, the analysis required the finding of the peak of the signals that coincided with the catastrophic tool failure.

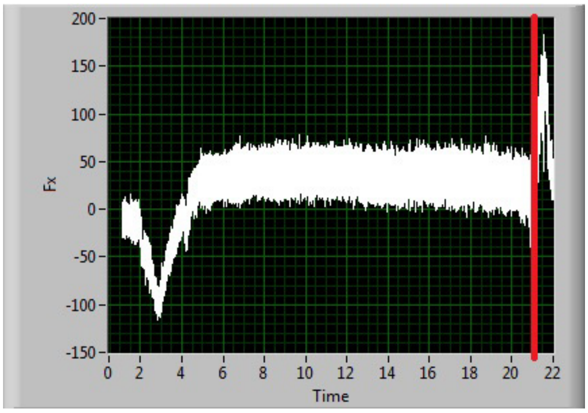
The second technique analysed the AE_{RMS} signals considering signal sub-portions of 100 samplings. For each sub-portion, the average was calculated. Afterwards, each average value was compared with the average value of the subsequent signal sub-portion. When the ratio between the preceding average value and the subsequent average value was higher than a threshold equal to 2, a CTF occurrence was identified. The corresponding time instant represents the time of CTF occurrence identified by the AE_{RMS} and the algorithm automatically stops.

However, as described in the following paragraph, the results obtained by processing the AE_{RMS} signal were less robust than those obtained from the analysis of the cutting force signals.

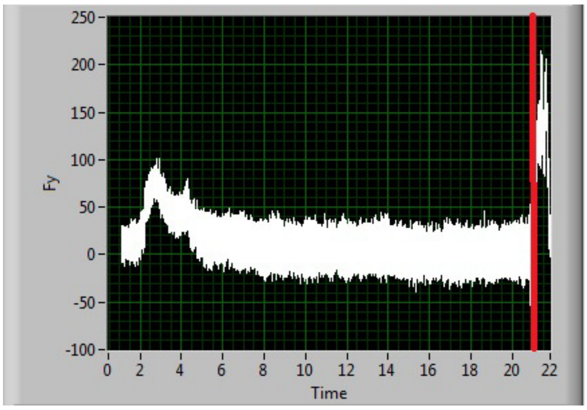
4. Discussion of results

Six recorded signals resulting from the machining process were analysed for CTF detection. Three of these signals were acquired when CTF occurred during the cutting process. The other three signals were acquired during normal cutting processes.

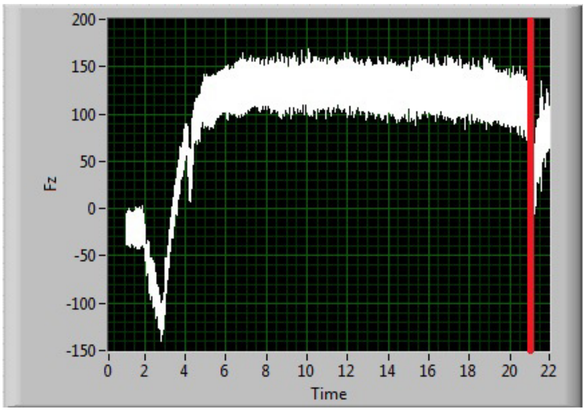
The processing of the cutting force signals allowed for the robust detection of CTF. The analysis of the sensor signals showed two different behaviours. In the first case, the methodology was able to correctly detect the exact instant of CTF occurrence in each of the three components of the cutting force (Fig. 5 a-c).



(a)

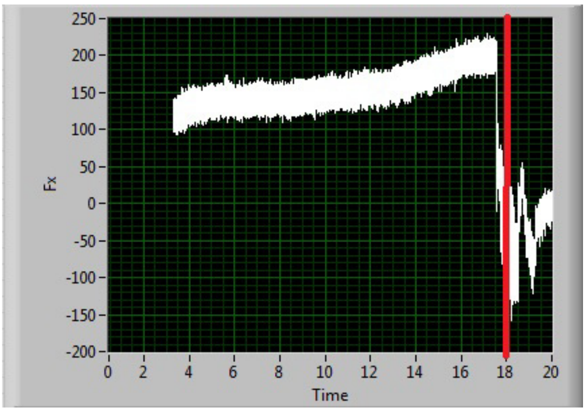


(b)

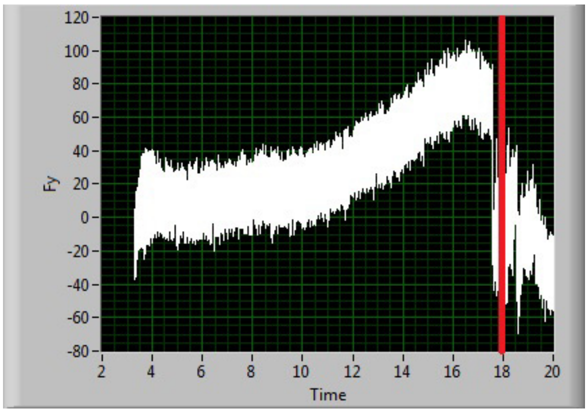


(c)

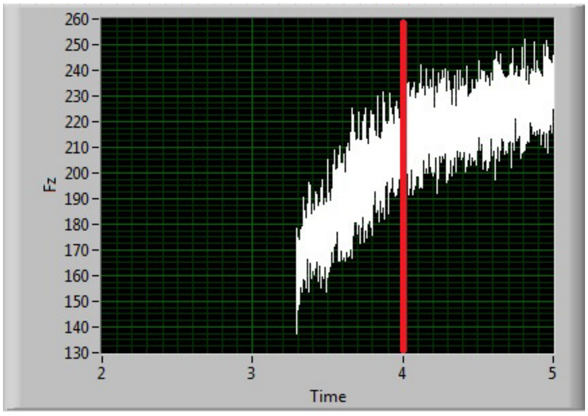
Fig 5. CTF detection in the same instant for all of the cutting force components: (a) F_x, (b) F_y, (c) F_z



(a)



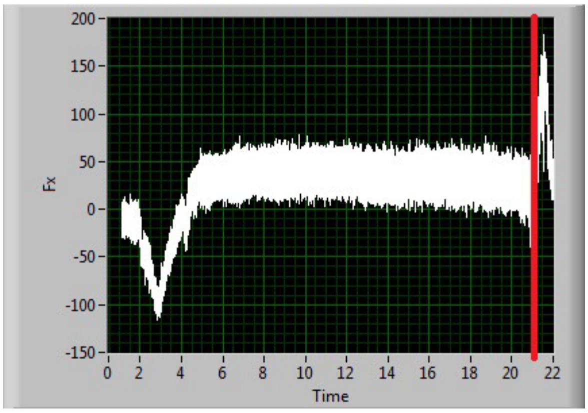
(b)



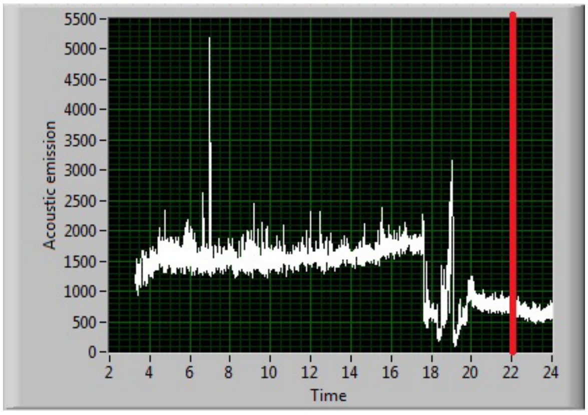
(c)

Fig 6. CTF detection with a two on three logic: (a) F_x, (b) F_y, (c) F_z

In the other case, the methodology of CTF detection could not identify the CTF occurrence at the same time instant using the three components of the cutting force (Fig. 6 a-c). In order to determine an overall instant of the CTF, at least two out of the three cutting force components signals need to provide a CTF detection. The use of this type of two out of three logic was necessary due to the fact that, in this methodology, the value of the threshold needs to be the same for all three signals.



(a)



(b)

Fig 7. Delay in CTF detection between F_x and acoustic emission signals

By analysing the signals in which the CTF was determined with a two out of three logic, a statistical approach was used to identify if there is one specific component of the cutting force that is less effective in CTF detection compared to the other two components. The analysis results showed that the cutting force F_z component is less reliable than the F_x and F_y components, as visible in Fig. 6-c, where the F_z signal behaviour actually produces a false alarm of CTF detection.

The acoustic emission signals were also analysed using the two methodologies explained earlier in order to detect the CTF instant and, subsequently, compare it with the CTF instant identified through the analysis of three components of the cutting force. The analysis showed that it was not possible to correctly detect the CTF instant for all the recorded signals due to a delay (~ 1 s) in the instant detection between the acoustic emission RMS and the cutting force components (Fig.19).

This was true considering both methodologies explained in the previous paragraph. In fact, in some cases the procedure was not able to detect a CTF occurrence in signals known to have CTF, while in other cases the detection was done with a high delay even of three or four seconds, which is unacceptable considering the aim of the research consisting in stopping the turning process in the moment of the CTF occurrence.

The procedure based on the analysis of the cutting force components was also tested on the acquired signals without the presence of a catastrophic tool failure, giving correct results in 100% of cases.

5. Conclusions and future developments

In this paper, a new methodology for the detection of catastrophic tool failure in turning processes based on multiple sensor monitoring was proposed and developed.

Sensor signals corresponding to the three components of the cutting force and to the acoustic emission RMS were acquired during experimental turning tests with different cutting conditions. The signals were subsequently analyzed and processed to automatically extract relevant features useful for CTF detection. Selected statistical features (signal mean, variance and kurtosis) were extracted over very small signal sub-portions of 100 samplings in order to enable the system to respond as quickly as possible during the turning process.

The methodology was developed using LabVIEW visual programming language in order to obtain an automatic procedure that could be used online during the turning process receiving input from the cutting force and the AE_{RMS} sensors.

The results indicate that the methodology is particularly robust when using as input data the statistical features (mean and variance) extracted from the cutting force sensor signals, while the procedure based on the acoustic emission features (mean, variance and kurtosis) shows in most cases a delay higher than 1 s in the detection of the CTF occurrence time instant.

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