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Development and Testing of a Combined Machine and Process Health Monitoring System

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Abstract

Process monitoring has been shown to be capable of observing the quality of a machining operation through sensor signals and analysis in both the literature and in commercially available systems. Some of these systems provide an additional benefit of monitoring the health of a machine tool. However, the commercially available systems tend to utilise relatively simple analysis techniques for both the process and machine health, limiting their application and robustness. Industrial interest in systems that can profit from the current advances in machine tool digitalisation and data analytics has grown considerably. This is especially true for the capability of early-detection of quality issues in components, whilst also ensuring machine tools are in a condition that can achieve high quality production. The present research includes the development and testing of a fingerprint routine which can be run at regular intervals to detect potential failure modes or machine tool degradation through signal analysis. Machining trials were carried out with the objective of detecting known defects in a workpiece through signal analysis. For both cases, a combined monitoring system was developed for data capture during testing, and a number of failure modes and defects were physically simulated to test the possibility of detection in the acquired signals. Time domain, frequency domain, and time-frequency domain signal processing techniques were applied to the sensor data with various levels of success. Continuous wavelet transforms (CWT) were of particular interest, as they successfully captured signal changes between tests for the physically simulated failure modes of the machine tool and the component. Therefore, a comparative CWT analysis was developed which successfully emphasised some of the machine tool failure modes and part defects when compared to baseline signals. The output of the comparative analysis may be well-suited to automation through machine learning techniques.

Keywords: Process monitoring; Machine health; Continuous wavelet transforms; Failure modes; Sensor fusion;

1. Introduction

Process monitoring allows the integrity of a machining operation to be gauged through any number of sensor signals, such as accelerometers, power/current clamps, or acoustic emission sensors. Collection of machine tool controller data provides additional data streams and can allow contextualisation of the sensor data. This methodology can help to identify issues with the component, cutting tool, or machine tool, before the component undergoes final inspection. The benefits of identifying issues in-process, rather than at final inspection, include limiting further damage to the component or machine tool, and preventing additional components being machined prior to identification of the issue. Installing such a system can therefore provide significant savings to a manufacturer in terms of scrap, machine tool maintenance, and downtime.

Commercially available process monitoring systems are often based on simple signal trending principals or static limits. As an example, the Marposs ARTIS Genior process

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monitoring system [1] monitors the level/amplitude of each sensor signal in isolation and creates an envelope for acceptable operating conditions by averaging over a minimum of five repeats of a particular process. Subsequent operations are then compared to these levels and customisable warnings issued if levels stray outside this envelope. This is a reasonable method; however, due to the minimal signal analysis, potentially significant process health indicators could be overlooked. The use of sensor fusion, ie evaluating combinations of sensor signals rather than in isolation, has also been suggested to provide more robust monitoring and fault identification. To gain further insight into the process and machine health, signal analysis techniques for feature extraction, such as kurtosis, fast Fourier transforms (FFT), spectral entropy and wavelets, could be employed [2-4]. Researchers like D'Emilia et al. [5] and Uhlmann et al. [6] extracted time domain features from acoustic emissions (AE) and vibration signals, and applied machine learning techniques, such as support vector machine (SVM), Bayes and nearest-neighbour to classify failure modes on rotational equipment. Similarly, Krishnakumar et al. [7] extracted standard error, kurtosis and median features to compare the classification accuracy of a decision tree and an artificial neural network for tool condition monitoring. Furthermore, wavelet transform techniques such as continuous wavelet transforms (CWT) have also been widely used for monitoring purposes. For instance, Sevilla-Camacho et al. [8] used CWT to illustrate the differences in vibration signals from 'healthy' and 'damaged' cutting tools. Likewise, Zhao et al. [9] used synchrosqueezing transforms, which is an extension of CWT, to classify faults in bearing systems through a convolutional neural network (CNN). However, none of the analysis techniques mentioned above are known to be in use in commercially available systems today, and so are seemingly confined to the literature.

A similar methodology can also be applied to machine health, allowing the condition of the machine tool to be gauged prior to cutting any material by conducting a fingerprint routine. This involves moving the machine axes, and/or spindle(s), in a pre-determined routine to allow the machine health to be evaluated and compared across frequent uses of the fingerprint routine. Movements by each axis are usually conducted in isolation whilst the machine is empty; providing a comparable signal where any issues detected can be easily attributed to the component that is in motion at the time of detection. It should be a relatively short routine, in this case 'short' was defined as no more than five minutes in duration; but include all of the vital motions of the particular machine configuration. This makes it feasible to run regularly (eg once per day or shift) and give confidence in the machine tool's performance during the periods between calibration events. Such a system is not intended to replace calibration procedures; but instead, provide brief and regular interim checks between each calibration.

Therefore, the motivation behind this research is to investigate the use of such techniques for machine and process health monitoring system that utilise a consolidated suite of sensors and machine tool data. This is intended to gauge the quality of the machining operation whilst cutting a component; as well as the machine tool's performance when not undertaking a machining operation, but instead conducting a fingerprint routine.

2. Experimental setup

The monitoring system used in this research consisted of two devices to capture vibrations and one power monitoring unit. For vibrations, one accelerometer (PCB 356A02) was mounted on the spindle and one accelerometer (PCB 604B31) was mounted on the machine bed, underneath the workpiece, by means of a Sensor Plate previously developed at the University of Sheffield AMRC[1]. The vibration signal was acquired using two NI-9234 modules at a sampling frequency of 51.2 kHz. The power monitoring unit was mounted on the spindle motor and the power signal was acquired using an NI-9223 module, sampling at 800 kHz. All of the data acquisition modules were plugged into an NI cDAQ-9178 and the signals were captured and recorded using LabVIEW. Parallel to this, machine data was acquired from the machine tool controller through MTConnect at 20 Hz.

The machine tool used throughout this research was a 5-axis DMG Mori DMU 40 eVo linear. Although most aspects of the system and the equipment used were generic for testing the fingerprint routine and the machining trials, some materials and tooling were specific for each. To test the fingerprint routine, the tools used included a calibration tool shown in Fig. 1 (a), normally used on the machine tool for laser tool setter calibration, the 'blank' tool shown in Fig. 1 (b), and the face mill cutting tool shown in Fig. 1 (c). For the machining trials, nine 100 mm x 100 mm x 40 mm, Ti-6Al-4V (β annealed) test vehicles were machined using micro-grain carbide inserts with a wear resistant PVD coating, mounted on a seven inserts tool holder. Fig. 2 shows the full machining configuration, including the fixturing used and the placement of the sensory equipment.

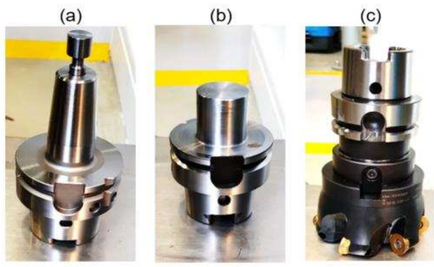

Fig. 1. (a) calibration tool; (b) blank tool; (c) face mill (heavy tool).

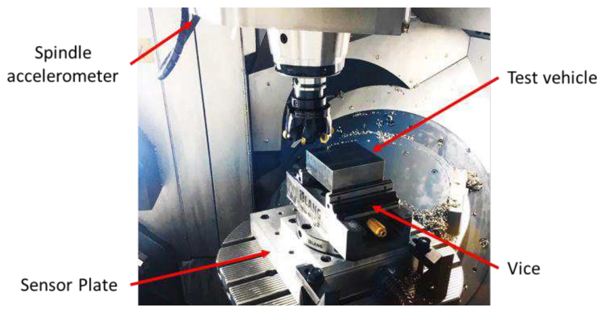

Fig. 2. Machining configuration.

[1] The University of Sheffield Advanced Manufacturing Research Centre with Boeing.

3. Experimental method

The fingerprint routine was designed to test each axis over the maximum amount of travel at various feed rates, and the spindle at various speeds. Whilst machining, it is rare that a machine tool will conduct motions that are limited to isolated axis movements. For this reason, the behaviour of the axis interaction during combined moves (diagonals and circles), as well as the interaction between spindle rotation and axis motion would normally be of interest. For this initial study, the routine was limited to isolated movements:

- Isolated linear axis moves – starting from a home location, run the X-, Y- and Z-axis to each extreme of travel sequentially, returning to the home location between each. This was conducted at feed rates of 8,000, 40,000 and 80,000 mm/min (corresponding to 10%, 50% and 100% maximum feed rate).
- Spindle rotation – at a home location run the spindle up to various speeds (20, 4,500, 9,000, 13,500, and 18,000 rpm) for five seconds at each speed, returning to 0 rpm between each.

Finally, to ensure all tests were directly comparable, the same tool was to be loaded whenever the fingerprint was run. Ideally, this should have been a tool that does not change over time through wear or breakage, ie a tool that does not get used for machining. Fortunately, the target machine has a calibration tool used for calibrating the laser tool setter (shown in Fig. 1 (a)). This is an ideal case as this particular tool is balanced to a classification of G 1.5 at 18,000 rpm and only ever used when being measured by the tool setter, ie it will not change over time.

The machining trials comprised of shoulder milling around the nine test vehicles. The machining parameters used included a spindle speed of 304 rpm, a cutting speed of 47.7 m/min, a feed speed of 361 mm/min, an axial depth of cut of 2 mm and a feed per tooth of 0.17 mm. This resulted in ten layers (axially) of cuts per test vehicle.

3.1. Failure mode and defect physical simulation

After a brief literature review and analysis, a number of relevant part defects and associated failure modes were identified, along with possible ways of physically simulating them on the workpieces. All reference to simulation of failure modes from hereon will be exclusively physical experimental simulation. Three criteria (potential risk involved, preparation simplicity and number of tests required) were then used to down-select these defects. This yielded three defects that were to be included in the testing: surface cracks (from workpiece defects or machining induced damage), tool wear, and misalignment.

The method of simulating surface cracks used has been demonstrated by Bauerdick et al [10], who prepared a number of workpieces with bores to emulate workpiece surface defects in a turning operation. For the purpose of these tests, the smallest drill suitable for cutting titanium was selected, which had a diameter of 1.85 mm. Three bores were drilled vertically on each affected test vehicle: two along one edge, and one along

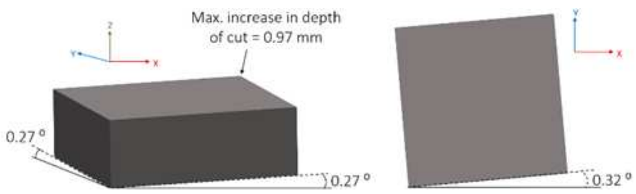

Fig. 3. Part orientation for misalignment machining trials.

the opposite edge; with the remaining two edges left unaltered to provide direct comparisons. These bores were offset by 5 mm from the edge to ensure they would be in the path of each pass of the shoulder milling operations.

Fresh tools were used for each test vehicle, other than test vehicles that were selected for 'tool wear' tests. Instead, these were machined with tools that had already machined another test vehicle. Finally, misalignment was introduced by tilting and rotating the worktable as shown in Fig. 3. This produced a maximum change in axial depth of cut of 0.97 mm.

Of the nine test vehicles, four were unaffected by defects (baseline); two with surface crack simulations; one misaligned; and two machined with worn tools.

Testing the detection capability of the fingerprint routine was more complex, as it required that a number of tests were conducted whilst the machine tool experienced some form of failure mode. As it was not feasible to alter or damage the machine tool in any way, a number of simulated failure modes had to be devised. These had to be within the normal operating capabilities of the machine tool, but should have affected its performance marginally during the fingerprint routine. A brief literature review yielded no suggestions on how this might be achieved, as the majority of testing in this area is conducted on a test bed rather than an entire machine tool. Instead, the simulated failure modes had to be devised from scratch.

The simulated failure modes, along with possible failure modes that each may represent, chosen for the testing are outlined in Table 1.

Table 1. Description of the simulated failure modes.

Simulation	Description	Example failure modes simulated
Heavy tool	Load a heavier tool than the calibration tool.	Incorrect tool loaded. Altered jerk/acceleration parameters. Spindle/axis drive fault.
Unbalanced	Tool with lower balancing classification than the calibration tool.	Increased spindle runout (eg issues with bearing/spindle taper/etc). Issue with calibration tool.
Cold	Conduct the fingerprint routine first thing in a morning.	Machine has not undergone necessary warm-up routine. Issue with ambient temperature.
Warm-up	Immediately after a warm-up routine has been conducted.	Issue with ambient temperature. Residual thermal effects due to heavy machining operations.
Feedrate-adjusted	Marginally reduced feedrate and spindle speed override.	Erroneous feedrate/spindle speed override. Machine parameters adjusted. Spindle/axis drive fault.

In total, 16 fingerprint routines were conducted. These comprised of three baseline, one heavy, two unbalanced, two warm-up, two feedrate-adjusted, three cold; as well as three

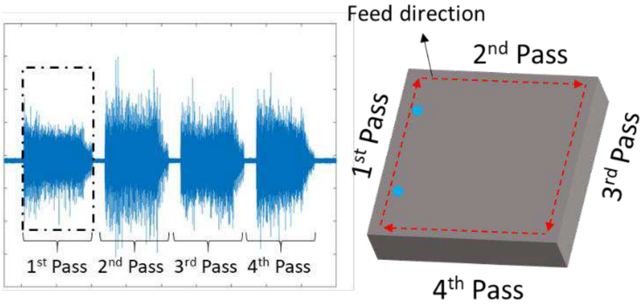

Fig. 4. Example of test vehicle machining signal segmentation for analysis with approximate bore locations highlighted in blue.

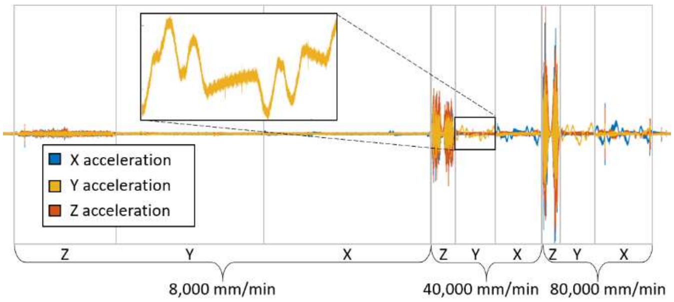

Fig. 5. An example of the linear axis fingerprint routine signal segmentation; including the isolated Y-axis acceleration signal from the 40,000 mm/min Y-axis motion.

additional 'post-machining' runs conducted immediately after three of the test vehicles had been machined.

3.2. Data preparation

To simplify signal analysis for comparison across tests and failure modes, all the acquired data was segmented. In the case of the machining tests, the data was segmented into milling passes. Fig. 4 shows the raw vibration signals of a single cut, which includes four shoulder-milling passes (one per square side) around the test vehicle. A full machining test included ten cuts, making a total of 40 passes for each test vehicle, and hence 40 datasets.

In a similar fashion, the fingerprint routine signal was segmented into each of the individual axis motions and spindle speeds. Fig. 5 gives an example of the spindle-mounted accelerometer signal recorded from a single linear axis fingerprint routine. It can be seen how each of these routines was segmented into each axis motion at each feedrate, resulting in nine individual segments.

4. Results and discussion

This section provides an overview of the successes and limitations of the analysis methods when applied to the data recorded during the machine trials. This section is not intended to be comprehensive, as a large number of tests with various parameters were conducted on the data in an exploratory fashion; resulting in varying levels of success. Instead, the general success of each method in highlighting differences between baseline and failure mode-affected trials is discussed.

4.1. Time and frequency domain analysis

The first set of analyses were done in the time domain, extracting signal kurtosis, single quantity RMS and single quantity mean for the vibrations and power signal in each test. Single quantity features can provide a simple summary of the signal behaviour for comparison between tests.

After this, the signals were transformed into the frequency domain using FFT for further analysis. Initially, this frequency-domain analysis was conducted manually by comparing the single-sided amplitude spectrum plots; but then a method of automatically extracting the dominant frequencies for each signal was developed.

Given the nature of the part defects tested during the machining trials, it was expected that the resulting increase in cutting forces, would in turn generate an increase in power and a less stable cutting operation. It was expected that these effects might be identifiable in both the time and frequency domain features extracted.

As can be seen in Table 2, this was not the case, and the signal extraction techniques were limited in their success; particularly when applied to the machining trial signals. It is thought that this could be due to the operations undertaken were not steady-state, and therefore cannot be simply characterized by single quantities. Instead, investigation into the time-frequency domain was conducted in an attempt to highlight how the signal components vary through time.

Table 2. Overview of feature extraction techniques.

Feature	Description	Outcome
	Time domain	
Kurtosis	Gives a value quantifying the heaviness of the tails of a (unimodal) distribution.	No apparent correlation with defects/failure modes found.
RMS	Gives the RMS value of the entire signal - ie a way to quantify the overall magnitude of the signal without negative components tending the average to 0.	No correlation found in the machining trials; but drop in RMS acceleration seen when spindle speed override applied during spindle rotation fingerprint routine.
Signal mean	Mean value of the signal.	No correlation found in the machining trials; but drop in mean acceleration identified when spindle speed override applied during spindle rotation fingerprint routine.
	Frequency domain (obtained through FFT)	
Dominant frequencies identification	Identifies the frequency and magnitude of the most significant peaks in a signal's FFT.	No correlation found in the machining trials; but changes in the single-most dominant frequency apparent across various failure modes.

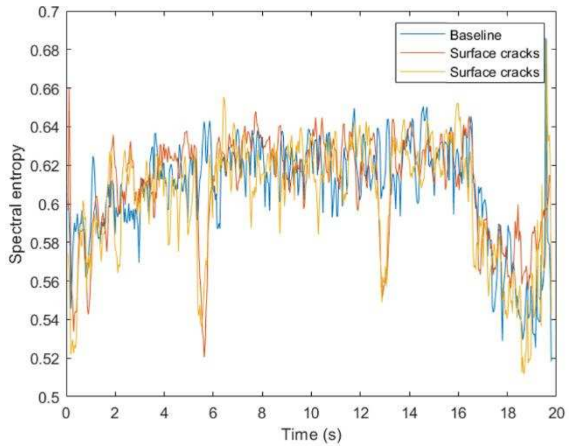

Fig. 6. Spectral entropy of the spindle accelerometer signal from two 'surface cracks' test vehicles compared with one 'baseline' test vehicle.

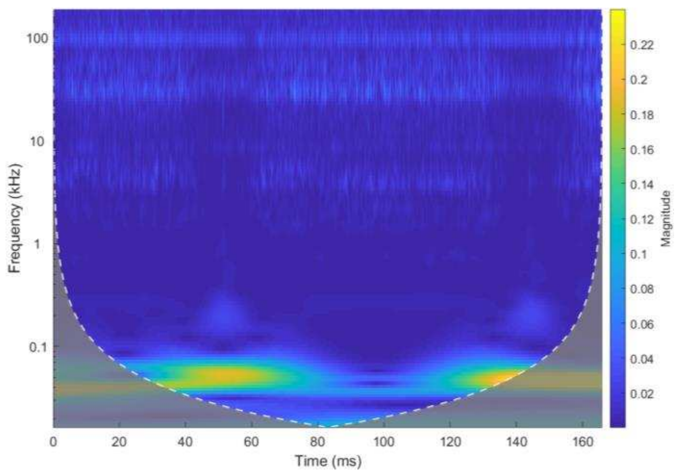

Fig. 7. A magnitude scalogram produced by performing CWT on the X-axis spindle acceleration signal during isolated linear X-axis move.

4.2. Time-frequency domain analysis

Spectral entropy analysis was applied to the machining signals to measure the complexity of each signal in the frequency domain throughout time. As can be seen in Fig. 6, the spectral entropy analysis results for surface cracks showed two distinct drops across all of the spindle accelerometer axes, which corresponded exactly to the moments when the cutting tool engaged the bores. However, no such distinction could be made for machining trials affected by misaligment or tool wear.

Another time-frequency domain analysis technique employed was CWT, an example of which is provided in Fig. 7. Although this technique is particularly useful in illustrating how the frequency components of a signal change through time; subtle differences between two similar signals are easily lost in the scalograms.

4.3. Comparative CWT analysis

To address the difficulty in identifying subtle differences between scalograms, a comparative CWT analysis technique was developed. The technique, illustrated in Fig. 8, followed these general steps:

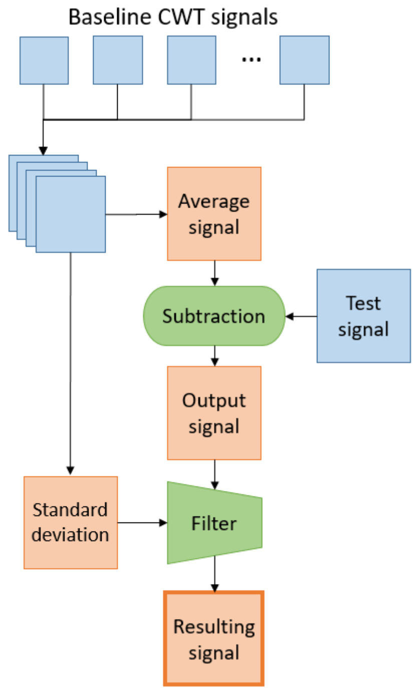

Fig. 8. Comparative CWT analysis flow diagram.

1. A number of baseline CWT signals are concatenated into a three-dimensional matrix.
2. Two matrices, one containing the average signal, the other containing standard deviation, are calculated across these baseline CWT signals.
3. A test signal is then subtracted from the average signal to produce an output signal, ie the difference between the expected signal and actual signal.
4. To account for the inherent variance in the baseline signals, the output signal is then filtered using the standard deviation matrix to produce the resulting signal.

The resulting signal only contains a residual, non-zero signal where the test signal strayed more than a pre-defined number of standard deviations away from the average signal. The pre-defined number of standard deviations could be adjusted to change the threshold/sensitivity of the filter.

The effectiveness of this technique when applied to an isolated linear axis fingerprint routine signal is illustrated in Fig. 9. Two baseline runs were used to test one routine with the feedrate override applied and one routine conducted post-machining, which should show little deviation. As it can be seen, there is a significant amount of residual signal in Fig. 9 (c) and very little residual signal in Fig. 9 (e).

Similar results were observed in the machining signals. Fig. 10 shows the implementation of this technique on a test vehicle affected by surface cracks, where Fig. 10 (c) shows the resulting signal, which accentuates the engagement of the cutting tool on the pre-drilled bores.

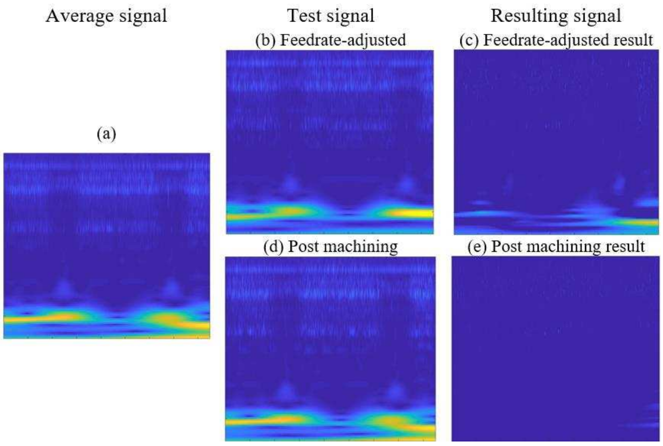

Fig. 9. Comparative CWT analysis applied to feedrate-adjusted and post machining isolated linear axis fingerprint routine signals.

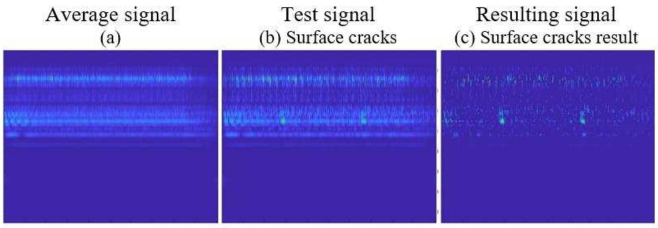

Fig. 10. Comparative CWT analysis applied to surface cracks machining trial signal.

Overall, this comparative technique showed good potential for the detection of machine faults and part defects, and it could be used as a feature extraction technique for further analysis. Two avenues might be suggested through this technique; the first regarding the use of machine learning, and the second the use of deep learning. For machine learning analysis, the raw values of the resulting CWT signals could be restructured and used in classification and regression techniques, eg SVM, decision forest and nearest-neighbour, to identify or measure machine and process failure modes. For deep learning analysis, the matrix structures or scalogram representations of the CWT signals could be used in CNNs for classification of the machine and part defects. An initial exploration of the latter approach has been initiated by the authors of this work, showing good potential which shall be investigated further.

5. Conclusions

The present research designed and tested a combined machine and process health monitoring system. This included the implementation of a fingerprint routine and machining trials to prove the concept of machine fault and part defect detection through sensor signals. To test this, both the fingerprint routine and machining of test vehicles were conducted under the influence of various physically simulated failure modes. A number of analysis techniques were tested with various levels of success:

- Most single-quantity time- and frequency-domain analysis techniques were unsuccessful in showing definitive correlations with the failure modes. This was attributed to the signals not originating from a steady-state process.
- Time-frequency domain analysis techniques of spectral entropy and continuous wavelet transforms (CWT) showed better correlations with the induced failure modes. However, spectral entropy did not exhibit clear results when applied to machining failure modes other than surface cracks.
- A comparative CWT analysis technique was developed which successfully filtered and highlighted signal elements related to the induced failure modes. This technique is proposed as a feature extraction method for further signal analysis using machine or deep learning.

Use of such a system within industry could assist in reducing the requirement for component inspection (ie a move towards ‘inspection by exception’) by inferring the process quality through the analysis of in-process signal data. It could also help reduce reactive maintenance events and unplanned downtime by detecting machine tool failure modes prior to machining operations.

Acknowledgements

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