Condition monitoring of manufacturing processes

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Abstract

Novelty Detection is an approach to classification that offers advantages over conventional techniques for monitoring high-integrity systems and manufacturing processes: it is not necessary to provide fault data to the system during development. Instead, providing a sufficiently comprehensive model of the system's normal behaviour has been formed, deviations from normal working conditions can be identified automatically. As information is discovered regarding the causes of these deviations it is then possible to move from novelty detection to diagnosis, but the ability to identify previously unseen abnormalities is retained at all stages.

This paper describes the results of an investigation for condition monitoring of a manufacturing process using techniques from novelty detection. We show that this approach allows the automatic identification of abnormal processes, providing identification of potential tool wear, giving advance notification of failure for the avoidance of bad processes.

1. Introduction

The investigation described by this paper applies techniques of novelty detection to a drilling manufacturing process, previously applied for novelty detection in high-integrity systems such as aerospace gas-turbine engines(1), large-vehicle turbochargers(2), and in the monitoring of human vital signs. We show that episodes identified as "abnormal" correspond to pre-cursors of eventual equipment failure, and that they can be used in the identification of faulty processes to avoid defects in production.

1.1 Previous work

One of the most well-established applications of machine learning techniques to monitoring manufacturing processes is that of neural networks, though they have been used in the multi-class classification (fault detection) manner, rather than for novelty detection. This requires examples of failure in order to accurately characterise particular modes of operation, which are difficult to obtain from high-value manufacturing processes. Approaches using such techniques include (3-9).

Approaches based on statistical pattern recognition using conventional multi-class classification include linear discriminant functions[(10)], autoregressive modelling[(11)], Hidden Markov Models[(12)], Kernel PCA[(13)], and Gaussian Mixture Models[(14)].

1.2 Data description

This paper illustrates the process by which novelty detection techniques are applied to data from a manufacturing drilling process, consisting of a number of similar tests. An automated drill unit was moved towards a static metallic disk at a fixed velocity ("feed-rate"), a hole was drilled through the disk, and then the drill unit was withdrawn at the same feed-rate. Parameters obtained from sensors affixed to the drilling unit as described in Table 1.

Table 1. Acquired Channels

Channel Number	Variable Name	Description
C1	A_x	Acceleration of the disk-mounting unit in the x-plane
C2	A_y	Acceleration of the disk-mounting unit in the y-plane
C3	A_z	Acceleration of the disk-mounting unit in the z-plane
C4	AE	RMS acoustic emission
C5	SP	Power delivered to the drill spindle

Test series for the drill bit contained initial periods of "normal" operation, followed by wear of the drill, and eventual drill failure. A description of the dataset examined is given in Table 2.

Table 2. Experimental Parameters

Test Numbers	Drill Rotation Rate	Feed Rate
[1, 190]	1700 RPM	80 mm/min

1.3 Pre-processing

In order to ready the dataset for analysis, pre-processing must be performed in order to remove artefacts from the time-series data that are unrelated to the condition of the manufacturing process during each test. In this case, it includes the removal of peaks in power spectra corresponding to an electrical power-supply, and the removal of transients and noise unrelated to system condition, such that meaningful diagnostic information contained with the data is retained for novelty detection. This latter is achieved by removing peaks in frequency spectra with amplitude below some assumed noise threshold.

2. Methodology and Results

2.1 Visualisation of original data

The use of numerous channels of data makes exploration of the time-series data difficult. Though each channel can be considered independently against time, it is difficult to identify changes in the relationships between channels. A dataset comprising channels of different data types (such as the vibration, acoustic energy, and power considered in the investigation described by this paper) forms a high-dimensional representation of the state of a system which is not readily interpreted by inspection. Visualisation techniques map high-dimensional data from their original space into a smaller number of dimensions (typically 2) to allow structure in the data set to be explored.

Here, we use the NeuroScale method[(15)] to map high-dimensional vectors (formed from the various channels of data described in Table 1) into two dimensions, for visualisation.

Figure 1 shows two-dimensional projections of high-dimensional data from a selection of tests. Data from the first third of each selected test are shown in green (in which the drill approaches the disk); data from the second third are shown in red (in which the drill enters the disk); data from the final third are shown in blue (in which the drill retracts from the disk).

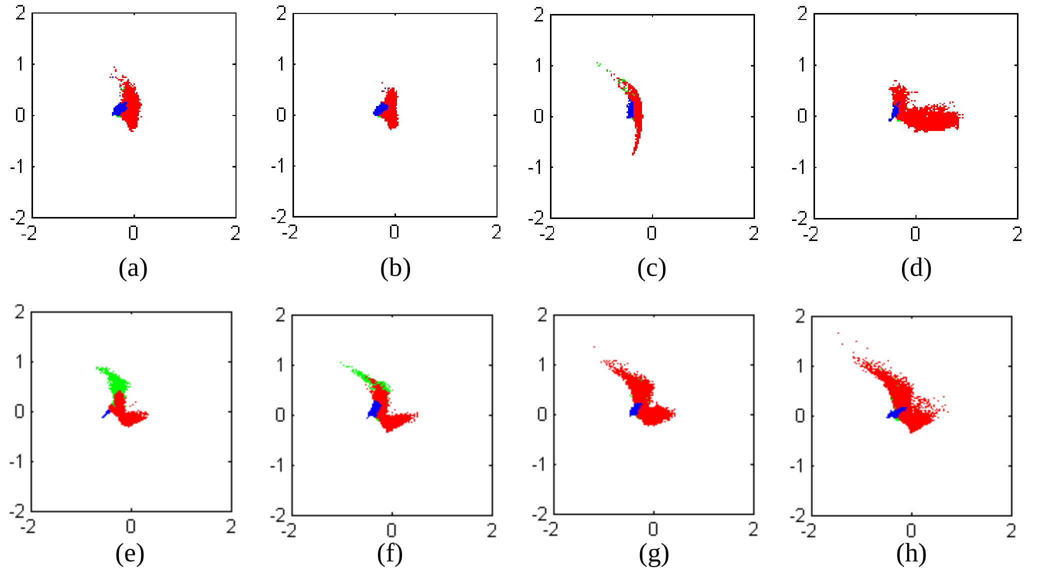

Figure 1. Two-dimensional projects of high-dimensional data from tests 39, 76, 77, 83, 115, 116, 124, and 127 shown in subplots (a) to (h), respectively. Note that NeuroScale projections have unitless axes.

Figure 1(a) and (b) show "normal" tests, in which projected data lie close to the origin in projected space. Figure 1(c) and (d) show data observed during movement of the acoustic sensor, which can be seen as excursions away from the origin. Figure 1(e) and (f) show tests in which tool wear is exhibited, while more significant wear is shown in Figure 1(g) and (h), corresponding to more significant deviations from the origin.

Thus, methods of visualisation allow "holistic" inspection of high-dimensional data in a single two-dimensional representation. Such techniques are also useful for the communication of the results of novelty detection to non-expert users of the system, providing a graphical interpretation of high-dimensional analysis.

2.2 Visualisation of derived data

This section describes an approach to novelty detection that allows automated off-line analysis of the manufacturing process to be performed, the results of which are compared to the insights gained from inspection of the dataset using visualisation.

The signature of a variable y throughout a test may be constructed with respect to the *operating point* of the system as illustrated in Figure 2. Here, the mean value of variable y observed throughout the test is plotted against the corresponding value of the operating point variable. This signature represents the variation of y across the range of the operating point throughout the duration of a test, which has been previously shown to characterise differences between "normal" and "abnormal" behaviour in other high-integrity systems containing rotating components[16,17].

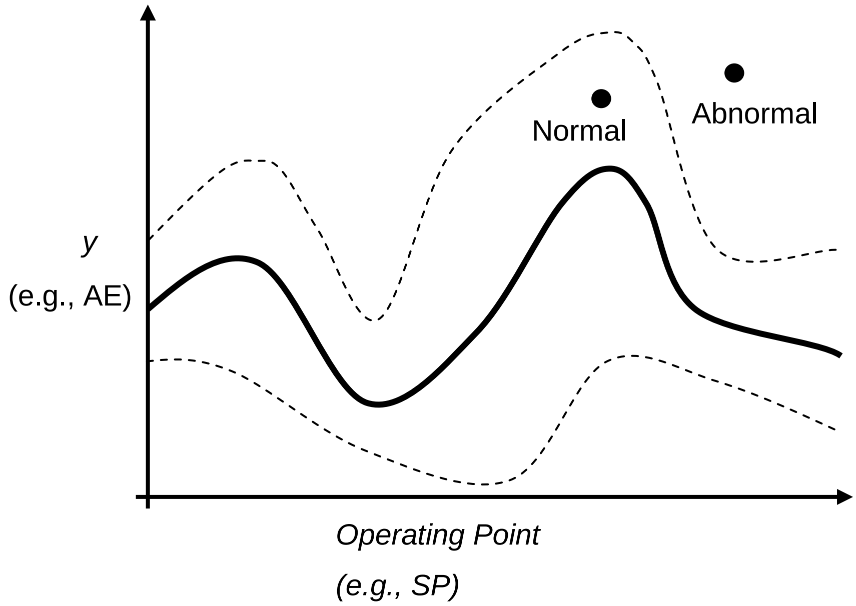

Figure 2. Constructing a signature of variable *y* over a range of an operating point variable. Signature mean and novelty thresholds are shown as continuous and dashed lines, respectively.

For the investigation described by this paper, *SP* was used as the operating point variable, quantised into $N = 10$ bins. This value of N was experimentally shown to be a good compromise between under-quantisation of the operating point (in which too few bins are used, resulting in little discrimination between signatures), and over-quantisation (in which too many bins are used, resulting in a large number of empty or under-populated bins).

Thus, for each test, a 10-dimensional signature for some quantity y can be constructed, characterising the variation of that quantity as a function of the operating point, *SP*. Each signature can be viewed as a 10-dimensional summary representation of a test, and may be compared to one another, in order to automatically identify signatures corresponding to "abnormal" behaviour.

The selection of quantity y used to construct signatures must be made such that differences between "normal" and "abnormal" manufacturing processes are characterised, and is referred to as a *feature* in statistical pattern recognition terminology.

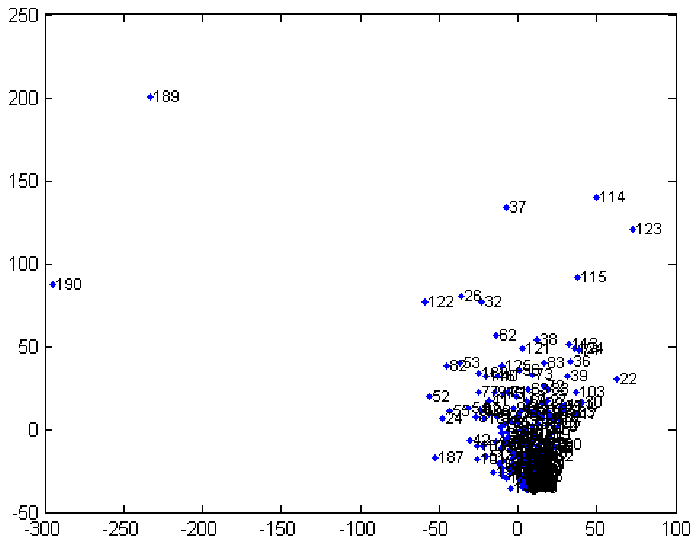

Figure 3. NeuroScale projection of 10-dimensional signatures for each test.

Figure 3 shows an example visualisation, in which *y* was chosen to be the peak energy in the power spectral density band [0, 6] kHz, after visual inspection showed that "normal" and "abnormal" tests exhibited differences in this feature. Note that practical systems based on this technology select more general sets of features, and that the above is shown for illustration of the methodology.

After projection from 10- to 2-dimensions, the majority of projected points lie in a single cluster about the origin, indicating that the corresponding tests from which the signatures were constructed were similar in terms of variable *y*. Significantly separated from the cluster of "normal" tests, tests 189 and 190 are shown plotted to the left of the figure. These tests were "abnormal", exhibiting significant tool wear that resulted in equipment failure.

2.3 Testing signatures

A *template signature* can be formed using similar techniques by collating observations from multiple tests. If these tests are selected to represent "normal" behaviour, the resultant template signature can be used to compare signatures constructed from later tests (as were visualised in Section 2.2).

Figure 4 shows Euclidean distances between signatures derived from each test, using methods described above, and the template signature constructed using data from tests [0, 40].

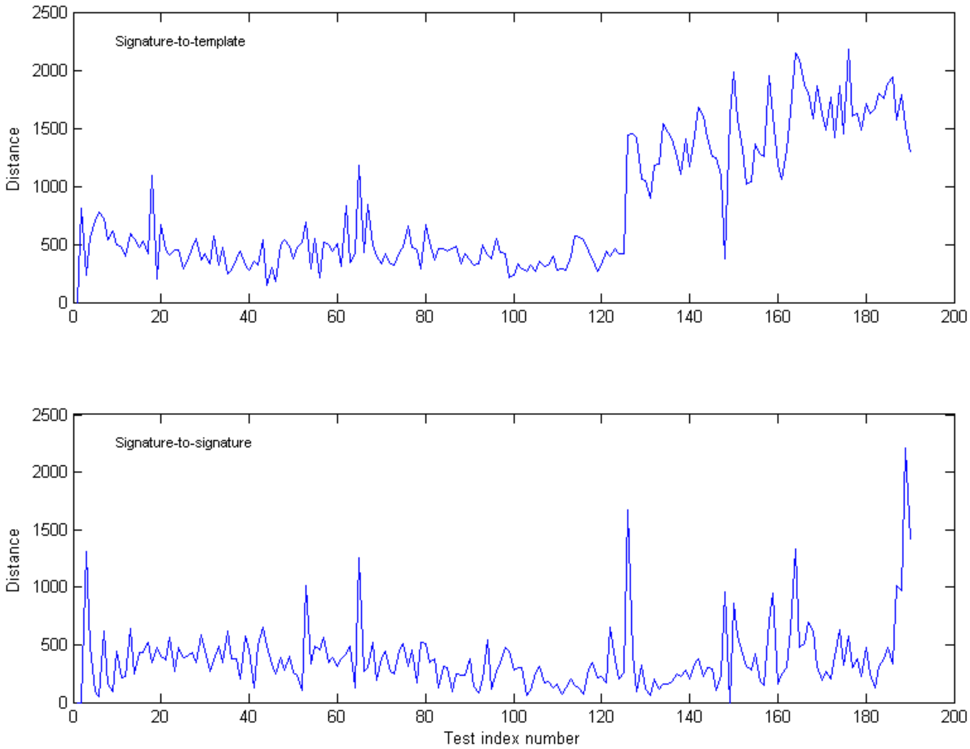

Figure 4. Signature-to-template (upper plot) and signature-to-signature (lower plot) distances for 10-dimensional signatures constructed from each test.

These signature-to-template distances are generally low for tests occurring near the start of the dataset, with transient increases at test 19 and 64. Significant increases in signature-to-template distances occur after test 125, as tool wear begins to occur. These distances generally increase with increasing tool-wear throughout the remainder of the dataset, indicating that this metric provides a useful discriminator between "normal" and "abnormal" tests.

Distances between successive signatures are shown in the lower plot of Figure 4, where large values are observed between signatures constructed using data from tests 124 and 125, when tool wear begins to occur. Further large increases in distance are observed between signatures at the end of the test, indicative of extreme tool wear and eventual failure. Earlier increases for tests 5, 53, and 64 were retrospectively determined to be due to changes in sensor configuration, which was fixed after test 64.

3. Conclusions

We have shown how "normal" and "abnormal" behaviour of a drilling process may be characterised using a novelty detection approach. Initially, visualisation techniques are employed to allow inspection of 5-dimensional data in a single plot. This allows the location of abnormalities within the dataset to be confirmed, and may inform the later use of novelty detection methods, and the selection of features that may allow automatic discrimination of “normal” and “abnormal” tests.

We have shown that a signature-based approach to analysis allows such abnormalities to be characterised, and that projection of high-dimensional signatures into 2-D can allow abnormal tests to be identified visually.

Automatic identification of signatures is possible by constructing a model of normality, and we have shown how an example distance metric between signatures and the model can be used to characterise abnormal drill behaviour, and potentially provide early warning of abnormal drilling operations.

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