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Analysis of the manufacturing signature using data mining

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A B S T R A C T

The use of data mining within manufacturing is a relatively modern application. Data mining can be used to find underlying links between the machining conditions, and parameters, and the final form of the part. Part of this procedure includes defining the form of the part, known as the manufacturing signature, which stems from all steps in the manufacturing process. In this paper, two potential definitions for the manufacturing signature of cylindrical objects are generated in terms of an analytical basis. The first description uses a simple Fourier description (known as lobing) and the second consists of a fully orthonormal description in terms of Forsythe polynomials and Fourier coefficients. Principal Component Analysis (PCA) is also partially used to investigate the underlying structure of the cylinders and investigate the connection between the analytical description and PCA. Experiments were carried out, machining thirty components under different manufacturing conditions (such as coolant pressure, tool length etc.). Data mining was then carried out on the process parameters, and either the amount of a given type of lobing or the classification of the cylinder in terms of the maximal lobing. The input to data mining for our case is either a numeric answer or a classification, which motivates the use of a simplified description. The use of PCA on this data set indicates a fundamental issue stemming from subsets of "similar" data which means dimensionality reduction is not possible in the usual way. The use of the analytical basis suggests a new sampling strategy to be used on certain geometries utilising Gauss-Legendre quadrature.

1. Introduction

The manufacturing process often leads to components which are distorted from the intended design. This distortion can be caused by many effects; machining conditions such as temperature or tool wear, material composition and grain structure, residual stress relaxation after manufacturing, post processing and multiple manufacturing steps, manufacturing method, part geometry, operator or machine tool path variation, and many more influences. The manufacturing signature [1] is also not simply the final manufacturing step, but a product of all of the steps which can lead to different types of distortion. There is also a measurement signature [2,3], which although typically minimal [4], influences the final observation of the part; for example in roundness testing it is known that the effect of off-axis measurement leads to a limaçon [5], which is then the fitted shape to correct for this measurement signature. Once a component is measured, there are two contributions which lead one to believe the component is not the same as the design; the manufacturing signature ("real" distortions), and the measurement signature ("observed" distortions).

In order to understand the manufacturing signature, there is a need to define the shape of components beyond that of standard metrological defined shapes. For example, for a flat plate, flatness is a description of the form error, but it offers no information about the shape of the plate. A greater understanding of the underlying shapes allows one to link the manufacturing conditions to the distortions, and arrive at a more optimal part through prediction and feedback. A simple classification of the form error (such as flatness) may also be minimised in the feedback loop, but in general can come from multiple sources unlike the underlying structure. Relaxing residual stresses tend to induce curling of flat plates, while a poorly overlapping tool path generates periodic structure in the surface. The flatness measurement only detects the *size* of the distortion, not any description therein [6].

The literature has recognised this need for a long time, and is hugely extensive; an excellent review can be found in [7] and more recently [1] which highlight the large number of areas where more advanced form fitting have been used. Specific to cylinders, the focus of this research, the standard description uses a Fourier-Chebyshev basis [7,8], Principal Component Analysis (PCA) [6], or lobing analysis [7,9,10], extended zone metttttthod [1,8]. This paper

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offers a similar approach, but focuses on an exact transformation of the data rather than least-squares error. This transformation affords a more detailed understanding of the distortion from the desired design, and can lead to a better understanding of the manufacturing process.

The final goal of classifying point cloud data in terms of a manufacturing signature is to use it for data mining. The use of data mining within manufacturing is relatively new, and comes with a large number of issues [8,11–14]. Here the focus is solely on the description of components in the context of data mining. The full measurement data is typically too dense for meaningful rule generation, while metrological characteristics are concerned with tolerances rather than form, and offer no understanding of the underlying distortion. Therefore, a simple yet meaningful description of the distortion of components could be used to generate predictive models of component quality [15]. It is important to note that using data mining techniques does not provide understanding of the underlying physics, but can find underlying correlations and mutual information in high dimensional data which link input parameters to the output.

There are two main findings from this work; a new measurement strategy and a failing within applying PCA in certain situations. Firstly, this analysis has elucidated the fact that the measurement process is the same as an overlap with the underlying structure, and therefore the optimal placement of measurement points (depending on the boundary conditions) are Gauss-Legendre points, or a uniform distribution. These sample points (and associated weights) then offer the optimum information about the underlying surface. The application of PCA has shown that it fails in certain situations, when there is a subset of data which is similar to itself, but different to the rest. When this is the case, the PCA vectors become dominated by this subset, and the top components are no longer sufficient to describe the full data set. The technique offered here, in terms of an exact basis, offers the same understanding of the distortions, and does not suffer this problem.

The experiment carried out in this work constitutes the training phase for data mining; initially data mining can be used to generate rules which are capable of predicting the distortions in the final part based upon the machining and environment parameters. These rules may then be used to choose optimal machining and measurement strategies, and updated with new data as the manufacturing continues.

This paper is organised as follows; in section II are the experiment details, sections III and IV describe the mathematical background to the basis used and Principal Component Analysis (PCA), sections V and VI are the results and discussion, and finally section VII is the conclusion.

2. Description of artefact, manufacturing process and measurement procedure

There were thirty components manufactured, each with eighteen drilled features and 4 milled features, which is depicted in Fig. 1. These components were manufactured at The Manufacturing Technology Centre Ltd (MTC) in Coventry on a DMG Mori 450. The eighteen (blind) holes were split in to four depths; 10 mm, 15 mm, 20 mm and 25 mm, and all were 6 mm diameter as depicted in Fig. 2. The external milled cylinders had diameters 100 mm, 105 mm, 110 mm and 115 mm, while the bottom cylinder was used for fixturing.

In order to induce variation between the features in a given component, the machining parameters were varied. Six machining parameters were included which were varied between features; peck-drilling (off, 1 mm or 2 mm), chip breaker (on or off), coolant pressure (off, small or nominal value), pilot drill (on or off), air blast (used instead of water coolant), step-down (two values of 2 mm or full cut). There are eighteen drilled features, and the four relevant variables were changed cyclically in patterns of six as indicated in Table 1.

For milling there were 4 features, and the three variables were changed as indicated in Table 2.

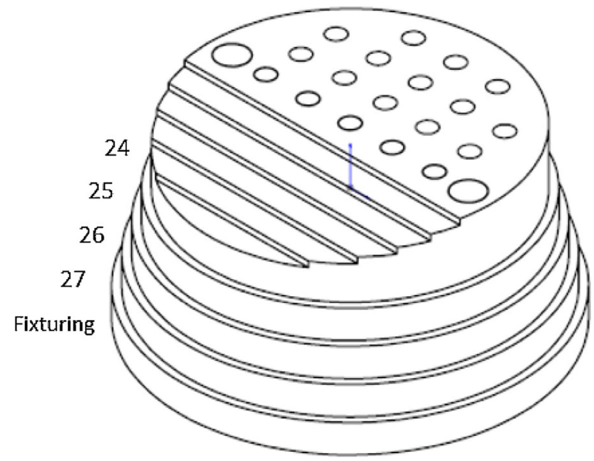

Fig. 1. Depiction of manufactured component. Numbers indicate the milled external cylinder nomenclature used.

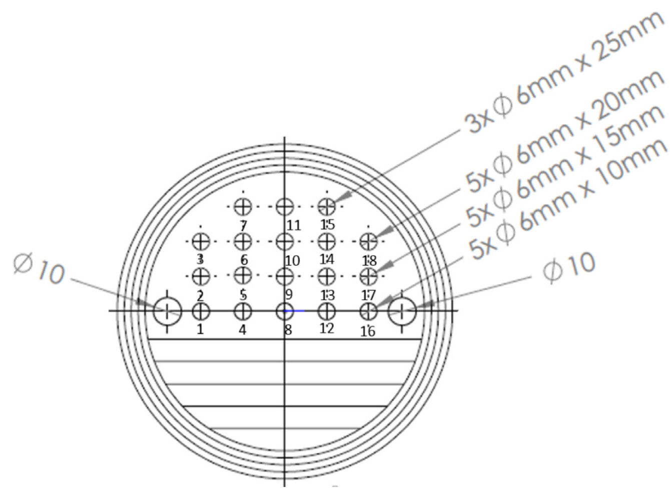

Fig. 2. Depiction of manufactured component from the top view. Numbers indicate the drilled cylinder nomenclature used.

Table 1
Manufacturing condition variables for drilled features.

Feature Number	Peck Drilling	Chip Break	Coolant Pressure	Pilot Drill
1, 7, 13	2 mm	Yes	Normal	No
2, 8, 14	2 mm	No	Normal	No
3, 9, 15	1 mm	Yes	Normal	No
4, 10, 16	1 mm	No	Normal	No
5, 11, 17	No	Yes	Lowest	No
6, 12, 18	No	No	Normal	Yes

Table 2
Manufacturing condition variables for milled features.

Feature Number	Step Down	Air Blast	Coolant Pressure
24	2 mm	No	Nominal
25	No	No	Lowest
26	No	No	Nominal
27	No	Yes	None