

## TOOL WEAR STATE CLUSTERING IN MILLING BASED ON RECORDED ACOUSTIC EMISSION

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**ABSTRACT.** It is widely accepted that tool wear has a direct impact on a machining process, playing a key part in surface integrity, part quality, and therefore process efficiency. By establishing the state of a tool during a machining process, it is possible to estimate both the surface properties and the optimal process parameters, while allowing intelligent predictions about the future state of the process to be made; thus ultimately reducing unexpected component damage. This state estimate can be achieved by implementing a variety of in-process monitoring techniques, and observing the development of selected data features as the wear state of the tool progresses. This paper explores the use of a principal component analysis (PCA) along with a multi-class support vector machine (SVM) to cluster a set of tools' wear states, based upon sampled acoustic emissions (AE) released during ball-nosed milling of Titanium-5Al-5Mo-5V-3Cr (Ti-5553).

**KEYWORDS:** Tool wear, acoustic emission, principal component analysis, support vector machine

### 1 INTRODUCTION

Over the past decade or so, acoustic emission (AE) has received, and continues to receive, a significant level of interest in the field of condition monitoring and process control. Acoustic emissions are caused by phenomena such as sliding friction at a flank-workpiece interface and the breaking of chips [1]; both of which are directly related to a cutting process and corresponding tool condition. AE therefore, has been used in a considerable amount of previous work for the monitoring of tool condition [2–7], surface roughness [8, 9], and event detection [1] to name but a few. AE based monitoring is also available from a number of commercial monitoring system suppliers [10]; however, it is often used alongside a range of different sensors in a data fusion approach [1]; the benefits of which include increased reliability, more robust decision making, and increased noise rejection. Such commercial systems are rarely successfully implemented, however, as they tend to target a wide range of processes with simple data processing methods and often fall short of the requirements set by industry; they also follow a diagnostic approach rather than prognosis of events before they happen [10].

In finish milling, the focus is largely on the surface of the part. Required roughness values are regularly given in product specifications, and maintenance of the surface finish within certain limits is considered crucial. As tool condition plays a significant role in surface generation, tools are, therefore, often replaced conservatively and rarely experience breakage. It is consequently desirable to determine

surface properties and tool state in-process; made possible using measured AE signals and the correlation between tool condition and workpiece surface integrity. By building relationships between the tool geometry, AE signals, and the workpiece surface, it is possible to begin to predict the future state of the process and make intelligent decisions about tool replacement, for instance. Recent developments in 3D scanning of tools allow a wide range of data to be collected relating to the tool's condition, providing a firm foundation for exploring correlations with gathered AE signals.

## 2 INDUSTRIAL CONTEXT

New civil aircraft platforms such as the Boeing 787 Dreamliner and Airbus A350 XWB, bring new manufacturing challenges, such as the ability to machine titanium alloys at rates that meet the increasing demands of cost down targets, increased volume and increased process capability. For the advanced manufacturing sector, this global drive towards increased productivity equates to not only higher surface speeds and machining rates, but better process understanding and the ability to avoid unnecessary machine downtime. Messier-Bugatti-Dowty develop, produce, and maintain both the nose and main landing gear for the 787, with approximately 50-60% of the total cost of production of these components resulting from the machining stage [11]. It is, therefore, evident that any time saving during machining will have a significant impact on the overall part cost to manufacture.

Within the machining stage, the finishing operation is considered the most time consuming as it lasts for approximately 50 hours with the same tooling set. One product in particular, the 787 truck beam, is machined from a solid forging of Ti-5Al-5Mo-5V-3Cr which brings with it new challenges due to the lower machinability of this material when compared to the high-strength steels used previously [12]. Such factors include its low modulus of elasticity, hardening characteristics, low thermal conductivity, and chemical reactivity at elevated temperatures [12]. Another example of one of the challenges faced when machining this alloy comes from the forging process. The forgings used for the 787 truck beams are some of the largest titanium forgings in the world, and as a result, can have a slight variation in material properties from end-to-end and around the circumference. This presents an issue when machining as calculating tool life and cutting parameters is directly dependant upon the material properties. Varying properties result in conservative cutting conditions and an element of the unknown when predicting tool life; as the harder the material, the faster the tools wear [12].

For Messier-Bugatti-Dowty (MBD), removing this uncertainty and maximising tool use is of utmost importance as it brings with it direct cost saving benefits and improves process efficiency. Utilising tools to their full potential without operator invention makes for a more automated, streamlined process, which is the end goal for any production environment. By making use of in-process monitoring and observed relationships between process variables, MBD aim to be able to perform online prediction of a tools state while gaining an understanding of the material properties of each individual truck beam that leaves the production line.

### **3 THEORY**

#### **3.1 Tool wear**

Tool wear is the change in physical state of a tool from its supplied condition to its condition after use. Depending upon both the tool and operation, this wear can consist of one or more different mechanisms which each result in various changes to observed signals. Flank wear is often considered the dominant and simplest to measure wear mechanism and is therefore investigated in detail in the previous literature [4, 13–16], often using a tool-maker microscope to obtain numerical values. Flank wear can also be predicted using Taylor's equation for tool life expectancy [17], another reason why it is commonly used in wear detection methods. This, however, is often not sufficient as it is typical for the dominant wear mechanism of a process to develop over time; from flank wear to crater wear for example. Flank and crater wear have been seen to mask the effects of one another in measured signals [18, 19], and thus any desired relationship between wear and monitoring signals is often difficult to establish for a longer process that experiences multiple wear types. By measuring 3D tool geometry, it is possible to gain more of an insight into a tool's wear state than has previously been possible.

The surface of a material following machining is a function of a number of factors including process parameters and tool condition [20]. It has been shown that flank wear of a tool has a direct impact on surface roughness [21] and considering that tool wear can be established from AE signals, it can be assumed that material surface properties can be inferred from those same AE signals [22]. Surface roughness is considered to be strongly related to the performance of a part in service [9].

#### **3.2 Acoustic emission**

AE has been widely used in the detection and monitoring of tool wear with successful results in both turning and milling operations [23–28] - partly due to the fact that the signal frequency of interest is much greater than that of the noise generated by the machine [6]. The previous work, however, appears divided when considering the signal processing strategy used. Both time and frequency domain analysis have their own benefits and drawbacks, often relating to the specific process of interest and which process parameters are expected to change. One of the most commonly-used features, the root mean square (RMS) value of the AE signal, is a measure of the power content of the signal that can be seen to increase with flank wear [6]. The downside of this, is that the RMS value is also associated with process parameters such as radial or axial depth of cut [29] and distinguishing the cause of an RMS change can be challenging; this often requires calibration on a per-process basis unless the process state remains constant. It has also been suggested that it is possible to isolate the effects of tool wear on the RMS value of the AE signal over a 10 second sample (AErms) by using a time domain averaging (TDA) technique [4]. This paper, as it focusses on a stable, repeated, periodic process, concentrates on time domain features including RMS, peak signal values, skewness, kurtosis, and mean values primarily. The time domain features are used as part of a principal component analysis (PCA) which, in turn, provides input data into a SVM.

### 3.3 Principal component analysis

Principal component analysis (PCA) has a number of different uses depending upon the desired outcome. Primarily, PCA is a tool for identifying patterns in data sets of high dimension where simply displaying the data in a graphical form is not possible. Once any significant patterns have been found in the data, redundant data can be discarded, enabling PCA to be used as a tool for dimensional reduction, data compression, variable selection, and data classification to name a few [30]. In this work, where a number of feature variables have been calculated, it is possible to perform a PCA to aid in both identification of the meaningful features, and creation of new features which represent the aggregate effects of the inputs. These new, more refined features can be used to define data points for clustering with an SVM.

### 3.4 Support vector machines

Support vector machines are explained well by Worden et al. [31] which includes a number of case studies. The idea behind SVMs for linear discrimination is that they select the hyperplane that separates the data and generalises best i.e. is furthest away from the data points in some sense [31]. SVMs are highly capable with regards to generalisation and this is desirable in the field of machine monitoring as they can provide high accuracy classification of tool and machine state [32]. SVMs can also give better generalisation results than ANNs when the training set has a limited number of samples, and can deal with very large feature spaces better than other methods [32].

Multi-class SVMs are needed when the problem is not a binary one and there are multiple types of failure for example. This is suitable for a machine monitoring situation where there are likely a number of classes. Three multi-class strategies are explained in [32] including one-against-all (OAA), one-against-one (OAO), and direct acyclic graph (DAG).

## 4 EXPERIMENTAL METHODS

### 4.1 Process Parameters

The test parameters used in this paper are taken from an industrial process and are intended to be representative of the operation used in manufacture. Using these parameters allows any gathered data and developed models to be directly applied and validated in a typical industrial environment. The parameters used are an axial depth of cut ( $A_p$ ) of 0.3mm, radial depth of cut ( $A_e$ ) of 0.7mm, spindle speed of 5082rpm, and feed rate of 4.268m/min. The experimental tool paths are also designed to be representative of the industrial process.

The aviation industry is gradually seeing a move towards increased levels of titanium components [33], and consequently, there is a significant research interest in increasing the efficiency of the manufacture of these components. For that reason, Titanium-5Al-5Mo-5V-3Cr (Ti-5553) is the material that will be used and referred to throughout this paper; an alloy used heavily in the manufacture of landing gear components.

## 4.2 Data Collection

The experimental machining trial used to develop the desired tool states and corresponding AE data was split into two parts. Firstly, nine tools were used to machine a solid billet for predetermined time intervals, consequently generating a selection of tools in different wear states. These tools could then be measured using an Alicona 3D optical microscope system to classify the various levels of wear and explore how the wear characteristics develop with time. Once the state of the tools was confirmed, the second half of the experimental trial was conducted using these tools to cut a material specimen while collecting monitoring signals from the process. This methodology provides information on the tool state, wear development with time, the effect tool state has on the signals generated during cutting, and the effect tool state has on the material surface. These correlations are explored further in Ref. [34].

Tool usage durations were chosen in half-hour increments, ranging from zero to three hours based on current usage data from the industrial process, and extended beyond the current limits to provide an overview of tool wear above and beyond that experienced during normal usage. As previously mentioned, the tool paths were designed to accurately represent those found in manufacture, resulting in the full cutting radius of the tools being utilised and maximising tool life. To achieve this, the tools lead angle is constantly changed while machining rings around a circular billet.

The second pseudo five-axis process machined a selection of test specimens taken from a Ti-5553 landing gear component, using the previously worn tools and collecting data from a number of different sources during the operation. An AE sensor was attached to the back of the workpiece fixture and the workpiece assembly was placed on a dynamometer, allowing both AE and force data to be collected simultaneously. It should be noted, however, that in an industrial environment, a dynamometer is not appropriate due to its intrusive nature and size limitations. This operation results in AE data relating to each of the tool usage durations, which in turn can be used for SVM state classification following a PCA. As close to 100% of the variance is accounted for in the first and second components, only these components will be used and treated as a dimensional reduction from the time-domain features originally calculated.

## 4.3 SVM clustering

Once a PCA has been performed, the first and second component scores can be plotted graphically to aid in identification of individual clusters. Using prior knowledge of the tool's wear state, each individual tool's data points can be grouped with other close data, resulting in a small number of clusters to train a supervised SVM with. In this work, four clusters are used representing new, used, worn, and damaged tools respectively.

## 5 RESULTS AND DISCUSSION

Figure 1 shows a plot of the first and second principal components following a PCA of the AE feature data. Each of the tools listed in the legend corresponds to a different tool in a different wear state, and is represented by a unique marker. It can be seen by the grouping of the different markers that the points calculated from each tool lie within close proximity to other points from that same tool while, in general,

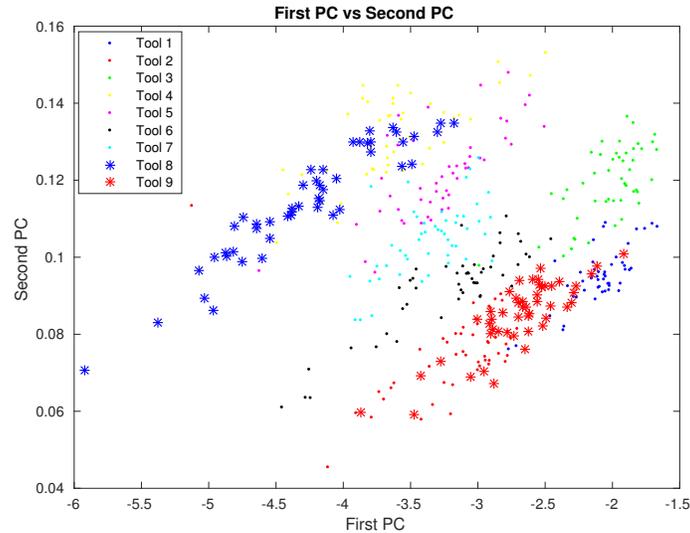


Figure 1: First versus Second principal component of the five-axis AE feature data.

points from different tools lie in clearly distinguishable areas. There are overlaps, for example, tool four and five which have points with small separations, however, despite this it appears possible to split the plot into a number of segments, relating to the various wear conditions present. In general, as tools become more worn (from tools one to nine), the points trend towards the top-left of the feature space, but again, there are exceptions to this such as the data for the most worn tool (nine), which can be seen mixed with that from tools one and two.

By splitting the data in Figure 1 into four separate clusters, it is possible to train a multi-class SVM using a one-against-all algorithm accordingly. Figure 2 and Figure 3 show the data used for training and testing the SVM respectively. Training and testing data was obtained by splitting the resulting PCA data into two smaller sets, and increasing the training dataset's size five-fold by applying a simple low-pass interpolation filter (it must be noted that this is not an ideal solution, and obtaining more data would be a more worthy solution). It should be noted that the data from tool nine is now hidden within the first cluster, and is indistinguishable from the brand new, less worn tools. For this preliminary work, we can assume that a tool must reach state four before progressing back to within the first, and any backwards trend can be ignored due to the fact that a tool cannot become less worn. Further work will be conducted, exploring other models for state prediction that do not suffer from this issue, for example hidden Markov models. It is expected that this apparent 'negative' wear is due to a combination of built-up edge forming on the cutting edge and in turn, reducing the cutting action and AE signals properties, or tool fracture/chipping, resulting in a sharp edge and less contact with the workpiece.

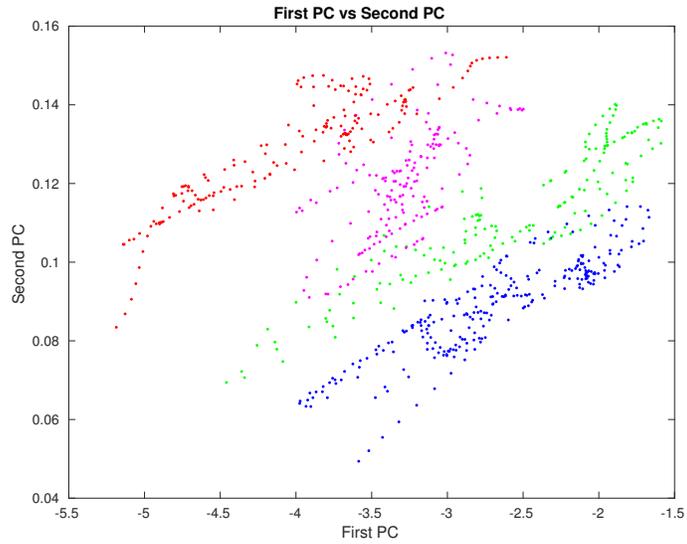


Figure 2: First versus Second principal component of the five-axis AE feature data, split into four clusters for SVM training.

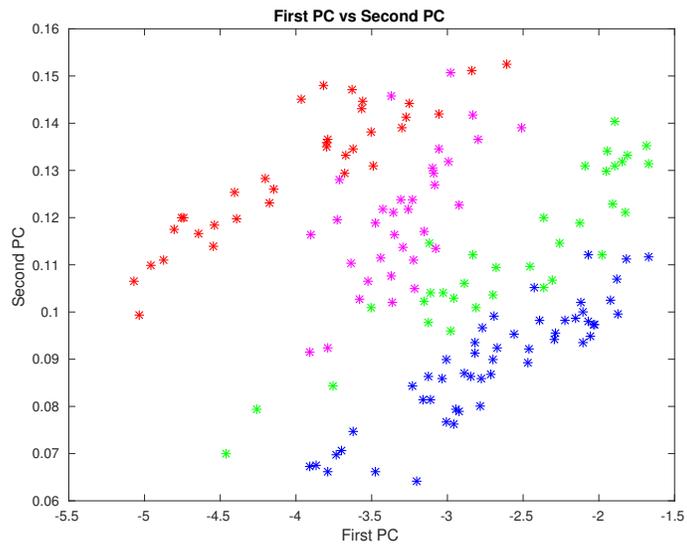


Figure 3: First versus Second principal component of the five-axis AE feature data, split into four clusters for SVM testing.

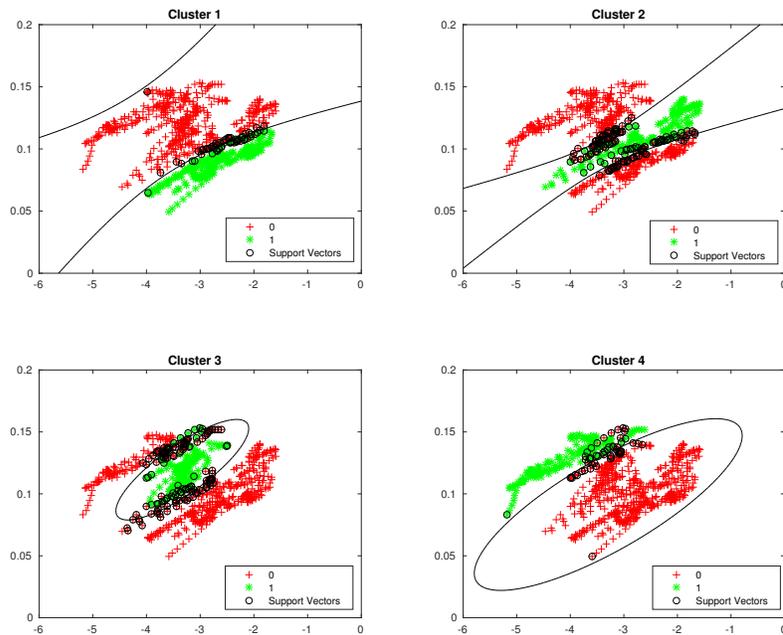


Figure 4: SVM vectors and clusters during SVM training.

The resulting decision boundaries and clusters following SVM training with a quadratic kernel function can be seen in Figure 4. When tested with the 153 test points, 133 of these were correctly classified, indicating an accuracy of 87%.

## 6 CONCLUSIONS

Clustering of incoming AE data features makes tool state classification possible using an SVM, and has been achieved with an 87% accuracy. While this all looks very promising, it is necessary to remember that the tool data used until now has been independent of time, and therefore, tool data for worn tools can appear in the same clusters as that of new tools. This poses a problem, as prognosis is not possible without a clear understanding of a tools condition and how it is expected to develop. Future work will therefore focus on prognostic models (including HMMs), with a view to accounting for the time-scale in which the incoming data is received when compared to previous state estimates.

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