Innovative signal processing for cutting force based chip form prediction

K. Jemielniak\textsuperscript{a}, R. Teti\textsuperscript{b}, J. Kossakowska\textsuperscript{a}, T. Segreto\textsuperscript{b}

\textsuperscript{a} Institute of Manufacturing Technology, Warsaw University of Technology, Narbutta 86, Warsaw, Poland
\textsuperscript{b} Dept. of Materials & Production Engineering, University of Naples Federico II, P.le Tecchio 80, Naples, Italy

Abstract
This paper reports on the activities of a joint research project work carried out by two Laboratories at the Warsaw University of Technology, Poland, and the University of Naples Federico II, Italy. The joint research work comprised the following main activities: (a) generation, detection, and storage of cutting force sensor signals obtained during sensor-based monitoring of machining processes with variable cutting conditions generating different chip forms, and (b) cutting force signal (CFS) characterization and feature extraction through advanced processing methodologies, aimed at comparing chip form monitoring results achieved on the basis of innovative signal analysis and processing.

Keywords: Chip form monitoring, Cutting force sensor, Advanced signal processing

1. Introduction

In this paper, the main activities of a collaborative research on chip form sensor monitoring based on cutting force signal analysis carried out jointly by two Laboratories, K. Jemielniak’s Lab at Warsaw University of Technology (WUT) and R. Teti’s Lab at the University of Naples Federico II (UN), Italy, are presented. These activities consist of:
(i) generation, detection, storage of cutting force signals (CFS) obtained during sensor-based monitoring of machining processes with variable cutting conditions yielding different chip forms;
(ii) examination and characterization of the CFS specimens with the aim of comparing chip form monitoring results achieved with diverse advanced signal processing and analysis methodologies.

The WUT volunteered in providing CFS specimens from turning tests under variable cutting conditions, using commercial instrumentation for cutting force detection and storage.

The CFS specimens were utilized by the WUT and UN Labs to perform investigations through advanced analysis procedures for CFS processing, characterization and feature extraction to achieve reliable chip form identification and monitoring.

This paper reports the characteristics of the CFS specimens and the investigation results obtained by the cooperating Labs, and presents the capabilities of the different advanced signal processing and data analysis methods for chip form prediction.

2. Experimental procedure

Cutting tests were performed at the WUT Lab through longitudinal turning of C45 (AISI 1045) steel with coated carbide inserts and variable cutting parameters, yielding different chip forms:
- cutting speed = 150, 250 m/min
- feed rate = 0.08, 0.13, 0.20, 0.30 mm/rev
- depth of cut = 1.0, 1.5, 2.0, 3.0 mm
Three cutting force components (F_c, F_f and F_p) were measured using Kistler laboratory dynamometer 9263, digitised at sampling frequency 2500 for 3 s (data sequence 7500 points). Each test was repeated three times. Chip form types (ISO 3685) \([1]\) obtained during the test are (see Fig. 1):

- 2.3 snarled tubular (unacceptable)
- 5.2 short, spiral helical (acceptable)
- 6.2 short, loose arc (acceptable)

3. Signal processing methodology

3.1. WUT Laboratory

At the WUT Lab, a particular form of wavelet analysis, Wavelet Packet Transform, was applied. In this method, each of the cutting force component signals (F_c, F_f, F_p) was split into a low frequency component, called approximation A, and a high frequency component, called detail D, both at a coarser scale. Then, the approximation and detail are further split into a second-level approximation and detail, and the process is repeated (see Fig. 2). The vectors of approximation coefficients and detail coefficients are called packets. Calculations were performed up to the fourth level yielding 30 packets for each of the 3 cutting force signals. A Debauchies 2 (db2) was used as mother wavelet. The analysis started at the first level of decomposition. Except for the direct packets (approximation A and detail D), their relative values were calculated as the ratio of the packet over the average approximation value $\mu_A$.

For each packet, several features were calculated: standard deviation ($\sigma$), variance ($\sigma^2$), moment of 3rd degree ($\sigma^3$), moment of 4th degree ($\sigma^4$), energy ($E = \Sigma \log(x_i)^2$). Then, all the values of each feature, obtained from all tests, were sorted according to the observed chip forms to identify the features that presented separate value ranges for different chip forms. If there was no such feature, the next level of decomposition, up to the third, was performed, followed by the same packet feature calculation. If, on any level, there was still no such feature, the best one (i.e. the one with the least overlapping range) and further four features were selected, each separating chip forms in different sets of test. Then, for each given test, the chip form was identified on the basis of features with values outside of the overlapping range.

3.2. UN Laboratory

At the UN Lab, CFS specimens were processed to achieve their spectral estimation through a parametric method \([2]\). In this procedure, the signal spectrum is assumed to take on a specific functional form, the parameters of which are unknown. Thus, the spectral estimation problem becomes one of estimating these unknown parameters of the spectrum model rather than the spectrum itself. From each signal specimen (measurement vector), $p$ features or predictor coefficients \({a_1, \ldots, a_p}\) (feature vector), characteristic of the spectrum model, are obtained through linear predictive analysis (LPA) \([2]\). Feature extraction was implemented through the application of Durbin’s algorithm \([2]\) with $p = 4, 8, 16$.

Neural network (NN) based pattern recognition was carried out in high dimensions feature spaces \([3]\) using the 4-, 8-, 16-elements feature vectors extracted from the CFS specimens through LPA. Three-layer feed-forward back-propagation NNs were built with the following architecture: the input layer nodes were equal to the number of input feature vector elements:

![Fig. 1. Chip form obtained in the experiments.](image1)

![Fig. 2. Three level wavelet packet; blacked fields indicate the frequency band of the original signal.](image2)
4, 8 or 16 (single cutting force component chip form classification), and 12 or 24 (combination of the three cutting force components chip form classification). The hidden layer nodes ranged from 4 to 64, depending on the number of input nodes. The output layer had only one node, yielding a coded value related to the chip form: 0 = {2.3} = snarled; 1 = {6.2} = short; 2 = {5.2} = short spiral.

NN training and testing was performed using training sets made of the 4-, 8-, 16- (single cutting force component) and 12-, 24- (integration of 3 force components) elements feature vectors, respectively. The leave-k-out method [2] was used: one homogeneous group of k patterns (here, k = 1), extracted from the training set, was held back in turn for testing and the rest of the patterns was used for training.

4. Results and discussion

4.1. WUT Laboratory

At the first level of decomposition, no signal feature enabled separation of single chip forms or, at least, acceptable (5.2 and 6.2) from unacceptable (2.3) chip forms. In Figure 3, example packet features at the first level are presented: variance of packet D (left) and variance of the ratio D/μA (right) for force component $F_f$. The second level of decomposition resulted in unambiguous recognition of unacceptable from acceptable chip forms that is critical for industrial applications. In Figure 4 two features are presented: standard deviation and variance of the relative packet AD for force component $F_f$. In both cases, the feature values for snarled tubular chip (2.3) are lower than for short spiral helical (5.2) and loose arc (6.2). Similarly, clear recognition was achieved at the third level of decomposition, shown in Figure 5.

Separation of loose arc from spiral helical chips seemed much more difficult. The ranges of all packet features up to the third level of approximation were overlapping (see Figs. 4 and 5). Thus, the five best features with the least overlapping range that enabled chip form separation in different tests were selected and presented in Table 1 and Figure 6. In Figure 6, the method of feature integration is explained using three cutting conditions designated as X, Y and Z with cutting speed $v_c$ = 250 m/min. Dotted bars indicate the feature value range for spiral helical chips, while hatched bars indicate the range for loose arc chips.
Dotted horizontal lines designate the feature value obtained in a specific test. If the line crosses one bar only, the feature recognizes the corresponding chip form. E.g., the energy of packet DDD for force component \( F_p \), \( E[\text{DDD}(F_p)] \), can recognize chip form 6.2 in test Y, whereas it is inconclusive for tests X and Z. Chip form 6.2 in test Y is also recognized by 3 other features: \( \sigma^3[\text{ADA}(F_f)] \), \( \sigma^3[\text{AAA}(F_f)] \) and \( \sigma^3[\text{ADD}(F_f)] \), and only \( \sigma[\text{DDA/ADA}(F_f)] \) is inconclusive. Thus, in test Y chip form 6.2 receives 4 “yes votes” and one “vote” can be considered as “abstaining”. The last mentioned feature is the only one pointing for chip form 6.2 in test Z, while the other features are inconclusive. Test X is an example where all feature values were in the overlapping range, i.e. inconclusive.

The summary of chip recognition results is shown in Figure 7. Numbers in squares corresponding to particular cutting parameters designate signal features “voting” for the recognized chip form. It is worth mentioning that separation of acceptable from unacceptable chip forms was 100% successful.

Table 1
Packet features selected for separation of loose arc (6.2) from spiral helical (5.2) chip forms.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Number of chip 5.2 recognitions</th>
<th>Number of chip 6.2 recognitions</th>
</tr>
</thead>
<tbody>
<tr>
<td>( E[\text{DDD}(F_p)] )</td>
<td>0</td>
<td>18</td>
</tr>
<tr>
<td>( \sigma^3[\text{ADA}(F_f)] )</td>
<td>12</td>
<td>6</td>
</tr>
<tr>
<td>( \sigma^3[\text{ADD}(F_f)] )</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>( \sigma[\text{DDA/ADA}(F_f)] )</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>( \sigma^3[\text{ADA/ADA}(F_f)] )</td>
<td>6</td>
<td>12</td>
</tr>
</tbody>
</table>

4.2. UN Laboratory

Cutting force sensor signal processing for feature extraction and NN pattern recognition analysis was carried out on the datasets to classify single chip forms based on cutting force sensor measurements. Experimental sensor data were respectively subdivided into 1500 points CFS specimens to construct full-bodied training sets comprising a total of 420 training cases. NN chip form identification was performed by inputting feature vectors from cutting tests with (a) fixed cutting speed (150 - 250 m/min) and variable feed rate and depth of cut, and (b) variable cutting speed, feed rate and depth of cut.
Fig. 8. Snarled/short/short spiral chip form identification for fixed (\(v_{c2}\)) or variable cutting speed (\((v_{c1}+v_{c2})\)) training sets, containing 210 or 420 training cases respectively, using a single cutting force component (\(F_c\)) or the integration of 3 cutting force components (\(F_c+F_f+F_p\)).

NN error vs. number of training pairs for: (a) \(v_{c2}\) and \(F_c\) with SR = 93%; (b) \(v_{c2}\) and \((F_c+F_f+F_p)\) with SR = 100%; (c) \((v_{c1}+v_{c2})\) and \(F_c\) with SR = 87%; (d) \((v_{c1}+v_{c2})\) and \((F_c+F_f+F_p)\) SR = 98%.

Furthermore, chip form identification was carried out through sensor data processing of single cutting force components (\(F_c, F_f, \) or \(F_p\)) and sensor data integration of the 3 force components (\(F_c+F_f+F_p\)). The NN output is correct if the actual output, \(O_a\), is equal to the desired output, \(O_d\), ± 0.50 % of the difference between adjacent chip form numerical codes, which was 1. By setting error \(E = (O_a - O_d)\), the chip form identification is correct if \(-0.5 \leq E \leq +0.5\); otherwise, a misclassification case occurs. The ratio of correct classifications over total training cases yields the NN success rate (SR). NN processing results can be displayed as in Figure 8, where error \(E\) is plotted vs. training cases for fixed (\(v_{c1}, v_{c2}\)) and variable cutting speed (\(v_{c1}+v_{c2}\)) training sets using single cutting force component (\(F_c\)) and the integration of the 3 cutting force components (\(F_c+F_f+F_p\)).

The figure shows that chip form prediction:
- does not improve for variable cutting speed (\(v_{c1}+v_{c2}\)) instead of fixed cutting speed conditions (\(v_{c1}, v_{c2}\)): in
the former case, misclassifications are not reduced in comparison with fixed cutting speed conditions for both single and integrated cutting force components; - improves by integrating the 3 force components \((F_c+F_f+F_p)\) instead of single components: in the former case, misclassifications are reduced in comparison with single cutting force component for both fixed and variable cutting speed conditions.

These results were verified for all NN data processing trials. In Figure 9, the NN SR is reported for fixed and variable cutting speed training sets processing for both single cutting force components and integration of the 3 components with reference to all chip forms considered together. It can be seen that the SR is higher when integrating the 3 components instead of using single components for both fixed and variable cutting speed training sets. This comes from a synergistic effect of the 3 force components that, if integrated, yield a SR higher than the maximum SR for each single force component. It is worth observing that the use of training sets comprising cases for all process conditions (variable cutting speed training sets) reduces the SR for both single force components and their integration (see Fig. 9). In fact, although variable cutting speed training sets are larger (420 vs. 210 training cases), the increase in number of variables has a stronger negative influence on the SR. In Table 2, the NN SR for single chip form identification is reported, showing that chip form prediction SR based on single chip forms separately is characterized by the same behaviour as the one for all chip forms together.

4. Conclusions

This paper presents the results of a joint collaborative work involving the analysis of cutting force signals, monitoring techniques and processing methods used by two Labs to predict the likely chip forms. This activity is carried out in view of the development of robust and reliable on-line, real time sensor monitoring procedures for chip form prediction of particular interest for practical industrial applications.

Acknowledgements

This research work was carried out with support from the EC FP6 NoE on Innovative Productions Machines and Systems – IPROMS and the Italian MIUR PRIN 2005 Project “ASMIM”.

References