Cognitive decision making in multiple sensor monitoring of robot assisted polishing

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Abstract

A multiple sensor monitoring system, comprising acoustic emission, strain and voltage sensors, was utilised during an experimental campaign of robot assisted polishing of steel bars for on-line evaluation of workpiece surface roughness. Two feature extraction procedures, based on conventional statistics and wavelet packet transform algorithms, were applied to the detected sensor signals in order to extract features to be fed to cognitive methods based on neural network pattern recognition paradigms seeking for correlations with the surface roughness of the polished workpiece.

Keywords: Polishing; Surface roughness; Sensor monitoring; Feature extraction; Sensor fusion; Neural networks

1. Introduction

Polishing is an abrasive surface finishing process that is widely used in diverse manufacturing industries such as aerospace, automotive, transportation, tool manufacturing [1]. Customarily, polishing is performed manually by experienced human operators and, for this reason, it is time-consuming, extremely skill-dependent, very costly, error prone and hazardous due to abrasive dust [2]. Automation is an appropriate response to overcome the difficulties resulting from hand-operated processes [3]. A novel semi-automatic polishing machine, the robot assisted polishing (RAP) machine, has been shown capable to eliminate the stochastic nature of manual polishing and improve the operation performance in terms of time compression and product quality requirements [4, 5].

Surface roughness measurement of the polished workpiece is usually performed by tactile instruments with a stylus linearly moving in contact with the polished surface to detect the stylus displacements, due to surface irregularities, as a function of position [6, 7]. This direct testing technique necessitates the stoppage of the polishing process to carry out the contact surface roughness measurements.

One powerful means to improve the performance, automation and quality of surface finishing operations, as well as for other advanced material removal processes, is the efficient on-line control implemented through sensor monitoring systems characterised by high robustness, reliability, reconfigurability and intelligence [8]. Diverse sensor types can be utilised for detection and analysis of process related signals, such as acoustic emission, cutting force, vibrations, motor power and current [9, 10]. Feature extraction algorithms need to be applied to the sensor signals in order to reduce the sensorial data dimensionality and achieve a synthetic signal characterisation, while maintaining the relevant information about the process conditions [9, 11].

Despite many investigations on the applications of cognitive decision making paradigms to machining process monitoring for purposes like tool wear prediction, chip form control, surface integrity assessment, etc. [12, 13, 14], to date an effective knowledge based system for improving the polishing operation performance and surface finish control of the polished workpiece is not available.

In this paper, a cognitive decision making support system based on multiple sensor monitoring for enhanced process control and reinforced operation repeatability and
predictability was developed for the robotic automation of polishing processes in the framework of the Zero-Defect Manufacturing (ZDM) EC FP7 "IFACOM" Project [15]. To this purpose, an experimental polishing campaign was carried out on AISI 52100 alloy steel bars with variable machining conditions using the robot assisted polishing (RAP) machine developed by Strecon A/S [16]. During polishing, acoustic emission (AE), strain and voltage sensors were employed for signal detection and analysis with the purpose of on-line process monitoring and control.

Two feature extraction methods, a conventional statistical procedure and a wavelet packet transform (WPT) algorithm [11, 17, 18], have been applied to the detected sensor signals to obtain relevant signal features to be fed to cognitive decision making systems. The latter employ neural network (NN) based pattern recognition paradigms [18, 19] to find the relationship between the input sensorial features and the best output assessment of polished surface finish after comparison with previously memorized input-output patterns [12].

2. Experimental tests

The experimental testing campaign was conducted within the activities of the FP7 European project (FoF NMP – 285489) - Intelligent Fault Correction and self-Optimizing Manufacturing systems (IFACom) [15].

The RAP machine by Strecon A/S was utilized to polish a 75 mm long AISI 52100 alloy steel cylindrical bar (Fig. 2) using a Gesswein #800 (MP800) polishing stone.

The polishing parameters selected for the tests were: main spindle rotational speed = 300 rpm; feed speed = 5 mm/s; polishing load = 1800 g or 1000 g; oscillation rate = 500 pulses/min; stroke length = 1 mm.

The polishing sessions were six, each with a duration of about 15 minutes and 50 seconds. Each polishing session consisted of 60 passes during which the full length of the alloy steel bar was repeatedly polished using:

- Session 1: 60 passes with 1800 g polishing load
- Sessions 2, 3, and 4: 60 passes with 1000 g polishing load
- Sessions 5 and 6: 60 passes with 1800 g polishing load

3. Multiple sensor monitoring system

During the polishing process, a multiple sensor system was employed comprising three diverse sensing units (Fig. 3):

- Acoustic emission (AE) sensor (Fuji Ceramics Corporation R-CAST M304A) mounted on the tool holder; the AE signals were pre-amplified, high-pass filtered with 50 kHz cut-off frequency, and digitized with 1 MS/s sampling rate.
- Strain gauge sensor located on the connection between the tool holder and the robot arm to measure the force generated during polishing; the strain signal was digitised with 50 kS/s sampling rate.
- Voltage sensor located in the electrical cabinet of the machine providing signals related to the motor power absorbance; the voltage signal was digitised with 50 kS/s sampling rate and then undersampled at 0.1 kS/s.

All detected sensor signals were digitised through National Instrument DAQ board NI 9232 and stored as text files with a variable number of samplings per file according to the sampling rate used for the related sensor signal type (Table 1).

4. Roughness measurements

The surface roughness of the polished workpiece was measured at the end of each polishing session. The roughness parameters considered were: $R_a$ (average deviation), $R_z$ (surface roughness based on the 5 highest peaks and lowest valleys over the entire sampling length), and $R_t$ (total height) [20]. The measurements were carried out on a Mahr profilometer (Fig. 4) by stopping the polishing process and dismounting the workpiece. Then, the workpiece was mounted again on the RAP machine and the polishing process was continued. The average value of the surface roughness parameters are reported in Table 2. It is worth mentioning that surface roughness measurements before polishing and after session 6 were not performed (Table 2).

![Fig. 3. RAP machine with the mounted sensor system: AE sensor and pre-amplifier, strain sensor, DAQ board. “Drop” indicates the utilised lubrication system.](image)

<table>
<thead>
<tr>
<th>Sensor unit</th>
<th>Number of samplings</th>
</tr>
</thead>
<tbody>
<tr>
<td>AE</td>
<td>131,072</td>
</tr>
<tr>
<td>Strain</td>
<td>16,384</td>
</tr>
<tr>
<td>Voltage</td>
<td>100</td>
</tr>
</tbody>
</table>

![Fig. 1. RAP machine.](image)

![Fig. 2. Workpiece: AISI 52100 alloy steel bar.](image)
5. Sensor signals analysis

5.1. Acoustic emission (AE) signals

One distinct character of AE raw signals in the time domain is that they are oscillation signals with a zero mean [21]. By examining the detected AE raw signals, a bias was noticed, most probably caused by electronic noise from the sensorial system, that produced a mean signal value different from zero. Signal pre-processing was therefore required to eliminate the bias from the detected signals and obtain proper zero mean AE raw signals. The pre-processing procedure was carried out using MATLAB® [17] and consisted of shifting each detected AE raw signal by calculating its average value and subtracting it from the original signal data to obtain the regular zero mean AE raw signal (Fig. 5 a).

The shifted AE raw signals were further processed by calculating the signal root mean square (RMS), with time constant 0.12 ms, in order to generate the matching AE RMS signals (Fig. 5 b).

Both shifted AE<sub>raw</sub> signals and AE<sub>RMS</sub> signals were submitted to the feature extraction procedures illustrated in the next section.

5.2. Strain and voltage sensor signals

The detected strain and voltage sensor signals did not need any pre-processing. Two example sensor signals of strain and voltage are plotted in Figs. 6 and 7.

6. Sensor signal feature extraction

The diverse sensor signals (AE, strain, voltage) were subjected to two signal processing procedures for aimed at feature extraction:

- Statistical feature extraction
- Wavelet packet transform (WPT) feature extraction
6.1. Statistical feature extraction procedure

The statistical features extracted from the AE, strain, and voltage signals were: mean, variance, skewness, kurtosis, and energy [22]. These statistical features were combined to construct two kinds of sensor fusion statistical pattern feature vectors, each including features from either AE raw signals or AE RMS signals (Table 3):

1) First kind of sensor fusion statistical pattern feature vector:
   - The vector elements consist of the statistical features extracted from the AE raw, strain, and voltage signals
2) Second kind of sensor fusion statistical pattern feature vector:
   - The vector elements consist of the statistical features extracted from the AE RMS, strain, and voltage signals

These pattern vectors were later employed as input vectors to knowledge based decision making paradigms.

Table 3. Statistical features from strain, voltage and either AE raw (upper row) or AE RMS (lower row) signals composing two kinds of sensor fusion statistical pattern vectors.

<table>
<thead>
<tr>
<th></th>
<th>Strain</th>
<th>Voltage</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>AE raw</strong></td>
<td>Mean, Variance, Skewness, Kurtosis, Energy</td>
<td>Mean, Variance, Skewness, Kurtosis, Energy</td>
</tr>
<tr>
<td><strong>AE RMS</strong></td>
<td>Mean, Variance, Skewness, Kurtosis, Energy</td>
<td>Mean, Variance, Skewness, Kurtosis, Energy</td>
</tr>
</tbody>
</table>

6.2. Wavelet packet transform feature extraction procedure

The WPT algorithm decomposes a signal into different components in different time windows and frequency bands through the wavelet scale function and scaled and shifted versions of a selected mother wavelet which is a prototype function [23]. Practically, it can be reduced to filtering the signal by high-pass and low-pass filters derived from the wavelet and scaling functions. At the 1st level of WPT, the original signal S is split into two frequency band packets called approximation, A, and detail, D. At the 2nd level, each approximation and detail packet are again split into further approximations, AA and AD, and details, DA and DD, and the process is repeated generating further decomposition packets [23, 24] (Fig. 8).

In this research work, the mother wavelet employed for the AE raw, AE RMS, strain, and voltage sensor signals is a Daubechies 3 denoted by “db3”. The decomposition was performed up to the 3rd level, yielding a total of 14 packets. For each packet, 5 features were calculated: mean, variance, skewness, kurtosis, and energy [22, 23].

The extracted features from the diverse sensor signals were utilised to construct sensor fusion pattern vectors of two kinds, each including features from either AE raw signals or AE RMS signals:

1) First kind of sensor fusion WPT pattern feature vector:
   - The vector elements consist of WPT features extracted from the AE raw, strain, and voltage signals
2) Second kind of sensor fusion WPT pattern feature vector:
   - The vector elements consist of WPT features extracted from the AE RMS, strain, and voltage signals

Overall, 14 packets × 2 kinds of sensor fusion WPT pattern feature vectors = 28 total sensor fusion WPT pattern vectors were obtained. Fig. 9 illustrates the two kinds of sensor fusion WPT pattern vectors constructed with the inclusion of WPT features extracted from either the AE raw signals (Fig. 9a) or the AE RMS sensor signals (Fig. 9b). These pattern vectors were later utilised as input vectors to knowledge based decision making paradigms.

7. Cognitive decision making based on neural network paradigms

The sensor fusion pattern vectors constructed with features from the diverse sensor signals (AE, strain, voltage) were employed as input vectors to a cognitive decision making approach based on neural network (NN) data processing. Artificial NNs, inspired by the biological central nervous system and in particular the brain, are composed of nodes that carry out parallel distributed data processing. The connections between these nodes determine the function of the NN. By adjusting the weights of the connections between the nodes, the NN is trained to perform a particular function. One key function that a NN can be trained for is pattern recognition, i.e. identification of patterns among the input features and their correlation with the desired output. The NN nodes are arranged in input, hidden and output layers [25].

A three-layer NN architecture [22, 26, 27] was implemented for each of the 30 input pattern vectors (28 sensor fusion WPT pattern vectors + 2 sensor fusion statistical pattern vectors) with a 15-45-1 configuration consisting of:

- One input layer with 15 nodes receiving the 15 features of each sensor fusion pattern vector;
- One hidden layer with 45 nodes;
- One output layer with 1 node yielding a binary value associated with the surface roughness: 0 = acceptable surface roughness, 1 = unacceptable surface roughness.

The NN training set was built up by coupling the correct binary target value with each of the signal files in order to map the input sensor fusion pattern vector to the output surface roughness acceptability. This was realised by setting a threshold surface roughness at Ra = 0.07 μm that represents the acceptable roughness level required from the polishing process [18].

The output of the NN decision making paradigm is a set of percentages, called success rates (SR). The SR of main interest for NN performance evaluation is the overall SR, defined as the ratio of successful NN mappings between input and desired output over the total number of testing instances [28].

![Wavelet tree with signal decomposition up to the 3rd level](Image)

Fig. 8. Wavelet tree with signal decomposition up to the 3rd level [23].
The overall NN SR is reported in Table 4 for each kind of sensor fusion statistical and WPT pattern vector. From the table, it can be noticed that the NN SR is in all cases very high, never displaying values under 90%.

As regards the behaviour of sensor fusion statistical pattern vectors, a higher SR is achieved for pattern vectors including statistical features from AE raw signals (93.56%) than for those including statistical features from AERMS signals (91.18%).

Concerning the performance of sensor fusion WPT pattern vectors, the highest SR is achieved for the AD packet (93.85%) containing features from AE raw signals whereas, by considering only the sensor fusion WPT pattern vectors containing features from AERMS signals, the highest SR is achieved for the DDA packet (93.44%).

8. Conclusion

A vital means to boost breakthrough improvements in manufacturing is the development and implementation of innovative sensor monitoring systems that are robust, reliable and above all intelligent. The application of cognitive paradigms based on artificial intelligence tools to sensor signals detected during manufacturing operations is a powerful instrument to achieve real-time decisions on the process under control.

The aim of this paper is the development of a cognitive decision making support system based on multiple sensor monitoring and sensor fusion technology to improve the quality and repeatability characteristics of polishing operations. For this purpose, an experimental campaign was carried out using a RAP machine to polish alloy steel bars by varying the polishing conditions. The multiple sensor monitoring system included AE, strain, and voltage sensors. Furthermore, polished bar surface roughness was measured after a predefined number of passes during the performance of the experimental testing.

Two feature extraction procedures based on conventional statistics and wavelet packet transform (WPT) algorithms were applied to the detected sensor signals: AE raw, AERMS, strain and voltage signals. The extracted features were combined to form sensor fusion pattern vectors to be fed to a cognitive decision making approach based on NN data processing.

By examining the performance of the two feature extraction methodologies, the NN success rate (SR) obtained for both statistical and WPT pattern vectors in the assessment of polished workpiece surface roughness level is particularly high: the SR is always > 90%, the more so for sensor fusion pattern vectors containing features extracted from the heftier AE raw signals. In addition, a typically superior capability of the advanced WPT feature extraction algorithm is observed in the exploitation of sensorial data knowledge content.

The distinctively high NN performance values achieved confirm that innovative signal analysis for feature extraction and selection is an effective and powerful method to implement robust pattern recognition procedures in practical...
machining sensor monitoring applications such as the on-line evaluation of surface roughness level in polishing operations.

Table 4. Overall NN SR for all 30 pattern vectors.

<table>
<thead>
<tr>
<th>Statistical features</th>
<th>AEraw, strain, voltage sensor signals</th>
<th>NN SR (%)</th>
<th>AEraw, strain, voltage sensor signals</th>
<th>NN SR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>WPT pattern feature vectors</td>
<td>WPT pattern feature vectors</td>
<td>NN SR (%)</td>
<td>Statistical features</td>
<td>NN SR (%)</td>
</tr>
<tr>
<td>A</td>
<td>92.85</td>
<td>A</td>
<td>90.63</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>91.58</td>
<td>D</td>
<td>91.52</td>
<td></td>
</tr>
<tr>
<td>AA</td>
<td>91.23</td>
<td>AA</td>
<td>92.45</td>
<td></td>
</tr>
<tr>
<td>DA</td>
<td>92.56</td>
<td>DA</td>
<td>91.56</td>
<td></td>
</tr>
<tr>
<td>AD</td>
<td>93.85</td>
<td>AD</td>
<td>90.75</td>
<td></td>
</tr>
<tr>
<td>DD</td>
<td>92.58</td>
<td>DD</td>
<td>91.23</td>
<td></td>
</tr>
<tr>
<td>AAA</td>
<td>93.12</td>
<td>AAA</td>
<td>90.32</td>
<td></td>
</tr>
<tr>
<td>DAA</td>
<td>91.47</td>
<td>DAA</td>
<td>91.23</td>
<td></td>
</tr>
<tr>
<td>ADA</td>
<td>90.57</td>
<td>ADA</td>
<td>92.65</td>
<td></td>
</tr>
<tr>
<td>DDA</td>
<td>91.56</td>
<td>DDA</td>
<td>93.44</td>
<td></td>
</tr>
<tr>
<td>AAD</td>
<td>91.23</td>
<td>AAD</td>
<td>91.81</td>
<td></td>
</tr>
<tr>
<td>DAD</td>
<td>92.91</td>
<td>DAD</td>
<td>90.88</td>
<td></td>
</tr>
<tr>
<td>ADD</td>
<td>91.19</td>
<td>ADD</td>
<td>92.26</td>
<td></td>
</tr>
<tr>
<td>DDR</td>
<td>93.61</td>
<td>DDR</td>
<td>92.85</td>
<td></td>
</tr>
</tbody>
</table>

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