TIME-FREQUENCY BASED SENSOR FUSION IN THE ASSESSMENT AND MONITORING OF MACHINE PERFORMANCE DEGRADATION

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ABSTRACT

Machines degrade as a result of aging and wear, which decreases their performance reliability and increases the potential for faults and failures. In contemporary manufacturing it becomes increasingly important to predict and prevent machine failures, rather than allowing the machine to fail and then fixing the failure. In this paper, methods of time-frequency signal analysis will be used to capture information from multiple machine sensors. This information could be used to assess machine performance degradation and subsequently take appropriate action. Signals emanating from three different sensors were collected when a sharp and a worn tool have been mounted on a CNC lathe machine. Several combinations of sensors and signal features have been tried in order to demonstrate the ability to use the information from multiple sensors and increase sensitivity to tool wear.

1. INTRODUCTION

It becomes increasingly important in contemporary manufacturing to predict and prevent machine failures, instead of allowing it to fail and then react to the failure. The impact of machine failure is such that this “predict and prevent (PAP)” paradigm is increasingly preferred and desired over the traditional “fail and fix (FAF)” paradigm. Therefore, there is a huge potential benefit in deploying a systemic methodology that will enable a near-zero-downtime performance, [1].

Machines degrade as a result of aging and wear, which decreases their performance reliability and increases the potential for faults and failures. The paradigm of machine degradation assessment was first introduced by Lee [2], [3], who used a Cerebellar Model Articulation Controller (CMAC) neural network [4], [5], to produce a quantitative confidence
value (CV) index of machine degradation. This approach enabled preventive maintenance through tracking and prediction of the CV index. The decreasing trend of this index was the quantitative indicator of machine degradation during its operation. One can identify the following advantages of the CMAC based approach to the problem of machine degradation assessment and monitoring.

a) Self-calibration: The CMAC neural networks have the ability to relatively quickly, without any outside intervention, learn the machine behavior during its normal operation and detect the abnormal states, without those states being presented to it previously.

b) Wide range of applications and generalization: CMAC neural networks have the ability to learn any function (machine behavior) in the training points to a desired tolerance. This ability allows one to use this approach in a wide range of applications

c) Sensor fusion: It is possible to merge inputs from several sensors mounted on the machine and use them concurrently to assess the machine performance.

These three properties enabled one to employ the CMAC based approach to continuous assessment and monitoring of the machine performance. Nevertheless, this approach has a number of weaknesses. Firstly, no signal processing method was applied to the CMAC inputs coming from the sensors attached to the machine. Raw signals were put into the network, which potentially could hamper the very function of the neural network if large signals of several thousands of samples were used as inputs into the network. Therefore, this approach was useful only for low-dimensional input feature spaces. Furthermore, the neural network architecture, as well as a wide range of CMAC neural network parameters need to be set by the user, and no general guidelines exist on how to do this. Currently, one must be an expert in the area of application in order to get any meaningful results out of the CMAC network. Finally, the CV index has been calculated in a rather ad hoc way, leaving the user with the task to interpret it and set thresholds that would trigger any action towards performing maintenance and fixing the problems identified by the CMAC network. This task becomes even more difficult if one takes into consideration that the CV index depends not only on the inputs into the CMAC neural network, but also on its architecture and parameters.

In this paper, a new method for processing and extraction of features from sensor readings is proposed for machine-tool degradation assessment and monitoring. It is based on the time-frequency signal processing tools and statistical pattern recognition. Implementation of the newly proposed methods is demonstrated in capturing information from multiple sensors mounted near the tool on a CNC lathe machine and using it to assess the tool condition. Signals were collected with a sharp and a worn tool mounted on the machine, and several combinations of sensors and signal features have been tested in order to demonstrate the generality of the proposed methods, and their ability to use information from multiple sensors to increase sensitivity to tool wear. The signal processing and feature extraction methods proposed in this paper will be used in the future to perform machine degradation assessment and monitoring, with the goal of maintaining the desirable properties a), b) and c) of the CMAC based approach, while alleviating its weaknesses outlined above.

The rest of the paper is organized as follows. The newly proposed combination of signal processing, feature extraction and pattern recognition methods for processing and fusion of sensory readings is described in Section 2. Description of the experimental procedure used for validation of the newly proposed methods is also given in. Section 3 presents experimental results of implementation of the newly proposed methods described in Section 2. These results are discussed in Section 4. Conclusions of this work and guidelines for future work are given in Section 5.

2. METHODS

2.1. Signal Processing Methods

Due to non-linearity and/or time dependency of the manufacturing process, signals emitted from rotary machines during operation are usually highly non-stationary [6], which invokes the need for the use of non-stationary signal analysis tools [7]. Time-frequency signal analysis tools are therefore suitable for processing of signals used for machine degradation assessment and monitoring.

Cohen’s general class of time-frequency distributions (TFDs) for the signal \( s(t) \) is described as

\[
C(t,\omega) = \frac{1}{4\pi^2} \int \int A(\theta,\tau) \phi(\theta,\tau) e^{-j(\theta + \omega \tau)} d\theta d\tau
\]

(1)

where

\[
A(\theta,\tau) = \int s^* \left( t - \frac{\tau}{2} \right) s \left( t + \frac{\tau}{2} \right) e^{j\theta t} dt
\]

is the ambiguity function of the signal, and \( \phi(\theta,\tau) \) is the time-frequency kernel [8]. The choice of the time-frequency kernel can be used to achieve desired properties in the resulting time-frequency representation. The bilinear nature of the two-dimensional signal transformation (1) causes the occurrence of cross-terms when multi-component signals are processed. Cross-terms are sometimes indistinguishable from the auto-terms and can hamper the time-frequency based signal interpretation and pattern recognition [9].

The Reduced Interference Distribution (RID) time-frequency kernels introduced by Jeong and Williams [10], suppress the TFD cross-terms by attenuating the signal terms away from the \( \theta \) and \( \tau \) axes in the ambiguity domain [11]. In addition to cross-term suppression, the RIDs retain a number of other desirable mathematical properties, which are not exhibited by other members of the Cohen’s class of TFDs, [10].

The binomial time-frequency kernel [12] is one of the RID kernels and is used in this paper to process signals obtained
from the sensors. Following [13], RIDs \( R(t, \omega) \) of the signals are viewed as probability distribution functions and are processed as their time-shift invariant representations (TIRs) as

\[
INV_T R(t, \omega) = R(t - E_R[t], \omega)
\]

where \( E_R[\cdot] \) denotes the mathematical expectation operator regarding \( R(t, \omega) \) as the probability distribution function. Frequency-shift and scale invariance were not pursued, because invoking those properties upon RIDs would interfere with their frequency content [15], [13]. The frequency content of the signal carries important information about machine performance and it should therefore be preserved for pattern recognition.

### 2.2 Feature Extraction Methods

When all moments \( E[Xt^pY^q] \), \( p, q \in N \) of a two-dimensional random variable \((X, Y)\) exist, its characteristic function \( f(u, v) = E[e^{i(uX+vY)}] \), \( u, v \in C \) can be represented as [8]

\[
f(u, v) = \sum_{p+q=0}^{n} \frac{j^{p+q}}{p!q!} E[X^pY^q] u^p v^q + o\left( u^2 + v^2 \right)^{\frac{n}{2}}, \quad n \in N
\]

where \( o(\cdot) \) is such that \( \lim_{h \to 0} \frac{o(h^n)}{h^n} = 0 \). Due to the unique correspondence between characteristic functions and probability distribution functions, Eq. (2) implies that moments of a probability distribution function can be used to describe it. TIRs of the RIDs can also be viewed as probability distribution functions and its moments \( M_{i,j} = E_{INV_T} [X_i Y_j] = \int \int \omega^j \omega^i INV_T (t, \omega) dtd\omega \), \( i, j = 0, 1, 2, \ldots \)

can be used in subsequent pattern recognition, similar to what was done in [14] and [15].

It is apparent from (2) that moments of order\(^2\) up to \( n \), completely describe the 2-D polynomial that, among all the polynomials of order up to \( n \), best approximates the characteristic function of a probability distribution function. Thus, the first few moments of a probability distribution function give the best indication of its general properties ([8], pp. 55).

### 2.3 Pattern Recognition Methods

Since time-frequency moments \( M_{i,j} \) described in Section 2.2 tend to be asymptotically Gaussian [13], one can model the machine behavior through the parameters of a multivariate Gaussian distribution function describing the distribution of the time-frequency moments collected during different stages of machine operation (training process). Usually, one can observe a high degree of correlation between the moments \( M_{i,j} \), and the uncorrelated portion of the information contained in the time-frequency moments can be extracted through the use of the well-known Principal Component Analysis (PCA), [16].

For the sake of completeness, the PCA procedure employed in this paper will be briefly presented. Let us assume that at a given machine operation stage \( S \) (in this paper, only the normal machine behavior and machine operation with a worn tool are considered), the signal features \( X \) are characterized by the multivariate Gaussian distribution with mean \( \mu_S \) and the covariance matrix \( K_S \). The symmetric matrix \( K_S \) can now be represented as

\[
K_S = \sum_{i=1}^{r} \lambda_i \vec{v}_i \vec{v}_i^T = V \Lambda V^T
\]

where \( r \) is the rank of the covariance matrix \( K_S \), \( \lambda_i, i = 1, 2, \ldots, r \) are the non-zero eigenvalues of \( K_S \), \( \vec{v}_i \) are the corresponding unit norm eigen-vectors and

\[
V = [\vec{v}_1 \quad \vec{v}_2 \quad \cdots \quad \vec{v}_r]; \quad \Lambda = \begin{bmatrix}
\lambda_1 & 0 & \cdots & 0 \\
0 & \lambda_2 & \cdots & 0 \\
0 & 0 & \cdots & \lambda_{r-1} \\
0 & 0 & \cdots & \lambda_{r}
\end{bmatrix}
\]

Due to the positive semidefiniteness of \( K_S \), all its eigenvalues are real and greater than, or equal to zero. Each eigenvalue \( \lambda_i, i = 1, 2, \ldots, r \) depicts the amount of the covariance matrix energy projected in the direction of the corresponding eigenvector \( \vec{v}_i \). When there exists a high degree of correlation among the components of \( X \), only a few of the eigenvalues in \( \Lambda \) account for most of the energy\(^3\) in the covariance matrix \( K_S \). Thus, assuming that eigenvalues \( \lambda_i, i = 1, 2, \ldots, r \) are arranged in descending order, (3) can be represented as

\[
K_S = \sum_{i=1}^{p} \lambda_i \vec{v}_i \vec{v}_i^T = V_p \Lambda_p V_p^T
\]

where

\[
V = [\vec{v}_1 \quad \vec{v}_2 \quad \cdots \quad \vec{v}_p]; \quad \Lambda = \begin{bmatrix}
\lambda_1 & 0 & \cdots & 0 \\
0 & \lambda_2 & \cdots & 0 \\
0 & 0 & \cdots & \lambda_p \\
0 & 0 & \cdots & \lambda_p
\end{bmatrix}
\]

\( p \) is the number of the principal components of \( K_S \), \( \lambda_i, i = 1, 2, \ldots, p \) are the largest \( p \) eigenvalues of \( K_S \), and \( \vec{v}_i \) are the corresponding unit norm eigen-vectors.

A query item \( \tilde{X} \) can now be transformed into a \( p \)-component random variable \( \tilde{Y} \) given as

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\(^3\) One can interpret this as only a few eigenvectors and eigenvalues accounting for most of the variability within the data class describing the machine state \( S \).
If \( \tilde{X} \) belongs to the class of signals from machine state \( S \), then \( \tilde{Y} \) should be normally distributed with zero mean and variance \( I_p \), where \( I_p \) is the unity matrix of order \( p \). Thus, for each query item \( \tilde{X} \), its adherence to the class \( S \) can be assessed through the Euclidean norm of the vector \( \tilde{Y} \), which in turn corresponds to assessment and classification based on the Mahalanobis distance of the query item from the training classes [17].

2.4. Experimental Procedure

Signals have been collected using a microphone, a vibration sensor and a force sensor mounted near the tool holder of a CNC lathe machine. A sampling rate of 20 kHz was used for all three sensors. 24 signals of length 0.25 ms (5000 samples each) have been collected when a sharp tool was used, and another 24 when a worn tool was mounted on the machine. The state of the tool was assessed using the ISO standard procedures, [18]. The TIRs of the RIDs of the signals have been produced as described in Section 2.1, and their moments of order up to 15 have been calculated as described in Section 2.2. Figure 1 and Figure 2 show several RIDs of the signals that have been collected and Figure 3 shows the moments of the TIRs of the signals from Figure 1. As can be seen in Figure 3, the size of the moments diminishes rapidly with the increasing order of the moments, and in this case it seemed that the ad hoc chosen number of moment orders was sufficient to describe the TIRs of the RIDs. Nevertheless, in the future, the issue of the number of moments necessary to describe a time-frequency distribution should be solved in a more systematic way.

3. RESULTS

Two sets of experiments have been conducted. In the first set of experiments, only the signals from normal process operation were presented to the classifier, and the cutting process degradation was assessed based on the drift of the newly arrived signals away from those observed during the training period (normal cutting process). In the second set of experiments, both the normal cutting process signals and the signals collected during operation with the worn cutting tool were presented to the classifier, and it was tested in performing a classical tool war monitoring task through recognizing the tool condition associated with the newly arrived signals.

3.1. Experiments assessing the drift away from the sharp tool machine operation

In the first set of experiments, the first 12 signals collected when a sharp tool was mounted on the machine have been used to train the classifier and assess the mean and covariance matrix of the signal features during machine operation with a sharp tool. Then, those signals along with the remaining 36 signals (total of 48 signals) were used to assess the drift of machine behavior from this normal machine state. The drift was assessed through the Mahalanobis distance of the signal features from the training signals, as described in Section 2.3. Figure 4 and Figure 5 show results of these experiments.

Figure 4 shows Mahalanobis distances of the TIR moments of the signal RIDs for signals collected during the machine operation with a worn tool (first 24 items) and with a sharp tool (the second 24 items). In the first experiment, TIR moments of order 1 through 3 (8 moments) from all three sensor signals have been used (total of 24 features). Results of experiments 2, 3 and 4 were obtained using TIR moments of order 1 through 5 (26 moments) of the signal RIDs from only the force, sound and vibration sensors, respectively (i.e. there was no sensor fusion, and in each case, the total of 26 features was used for classification).

Figure 5 simultaneously shows the first two principal components for each of the 48 signals used in the four experiments described above. It visually illustrates the class separation when different combinations of signals and signal features are used. Experiments 1, 2, 3 and 4 in Figure 4 correspond to plots a, b, c and d, respectively, in Figure 5.
3.2. Experiments in distinguishing between a sharp and a worn tool

The second set of experiments was carried out with 12 training items added to the previous training set in order to inform the classifier about the worn tool machine operation and test it in detecting this abnormal machine state. The 24 training signals (12 from the operation with a sharp tool and 12 from the operation with a worn tool) have been added to the remaining 24 signals that were not used in training, and the ability of the classifier to use the Mahalanobis distance from the classes in the training set to distinguish between the two states of machine tool has been tested.

Four experiments have been conducted with the training set described above. In the first experiment, TIR moments of order up to 3 from all three sensors have been used (total of 24 features). In the second, third and fourth experiment, TIR moments of order 1 through 5 of the signal RIDs (total of 26 features) from the force, sound and vibration sensor readings, respectively, have been used. Figure 6 shows Mahalanobis signal distances calculated as described in Section 2 from training signals collected during the machine operation with a sharp tool and the training signals collected during the machine operation with a warn tool. As in Figure 4, the first 24 items represent machining operation with a worn tool, and the second 24 items represent machining operation with a sharp tool.

In the first experiment, no misclassifications have been observed (100% correct classification). In the second experiment, 10 misclassifications occurred (79.2% correct classification), and in the third and fourth experiment only one misclassification occurred (97.9% correct classification). More detailed classification results are given in Table 1.
Figure 4. Mahalanobis distances of the TIR moments of the RIDs of the signals collected during the machine operation with a worn tool (items numbered 1 through 24) and with a sharp tool (items numbered 25 through 48). In the first experiment, TIR moments of order 1 through 3 from all three sensor signals have been used.

Figure 5. Plots of the first two principal components for each of the 48 signals used in the tests from Figure 4. Experiments 1, 2, 3 and 4 in Figure 4 correspond to plots a, b, c and d, respectively. The circles denote principal components of the TIR moments produced from the signals collected during machine operation with a sharp tool, while the asterisks denote principal components of the TIR moments produced from the signals collected during machine operation with a worn tool.

Figure 6. Mahalanobis distances for experiments 1, 2, 3 and 4 from section 3.2. Plots a, b, c and d correspond to experiments 1, 2, 3 and 4, respectively. The solid lines denote Mahalanobis distances from the training signals on the sharp tool machine operation, while the dotted lines denote Mahalanobis distances from the training signals on the worn tool machine operation.

Table 1. Classification results for experiments 1, 2, 3 and 4 from Section 3.2.

<table>
<thead>
<tr>
<th></th>
<th>Sharp tool operation</th>
<th>Worn Tool Operation</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training Items</td>
<td>12</td>
<td>12</td>
<td>24</td>
</tr>
<tr>
<td>Total Items</td>
<td>24</td>
<td>24</td>
<td>48</td>
</tr>
<tr>
<td>Correctly Classified</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experiment 1</td>
<td>24 (100%)</td>
<td>24 (100%)</td>
<td>48 (100%)</td>
</tr>
<tr>
<td>Experiment 2</td>
<td>21 (87.50%)</td>
<td>17 (70.83%)</td>
<td>38 (79.17%)</td>
</tr>
<tr>
<td>Experiment 3</td>
<td>23 (95.83%)</td>
<td>24 (100%)</td>
<td>47 (97.92%)</td>
</tr>
<tr>
<td>Experiment 4</td>
<td>23 (95.83%)</td>
<td>24 (100%)</td>
<td>47 (97.92%)</td>
</tr>
<tr>
<td>Misclassified</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experiment 1</td>
<td>0 (0%)</td>
<td>0 (0%)</td>
<td>0 (0%)</td>
</tr>
<tr>
<td>Experiment 2</td>
<td>3 (12.50%)</td>
<td>7 (29.17%)</td>
<td>10 (20.83%)</td>
</tr>
<tr>
<td>Experiment 3</td>
<td>1 (4.17%)</td>
<td>0 (0%)</td>
<td>1 (2.08%)</td>
</tr>
<tr>
<td>Experiment 4</td>
<td>1 (4.17%)</td>
<td>0 (0%)</td>
<td>1 (2.08%)</td>
</tr>
</tbody>
</table>
4. DISCUSSION

It is apparent from Figure 4 that Mahalanobis distances of the TIR moments of the signal RIDs for the signals collected during machine operation with a sharp tool (item numbers 25 through 48) are smaller than those of the TIR moments of the signal RIDs obtained when the tool was worn (item numbers 1 through 24). This increase in Mahalanobis distances when tool conditions drift away from the ones that were observed during training, can be used for early detection and preventive maintenance, which is the ultimate goal in Intelligent Maintenance Systems, [1]-[3].

Furthermore, one can see that the signals that are numbered as item numbers 40 and above demonstrate an increasing trend in their Mahalanobis distances from the training set. The reason for this trend is that these signals have been collected when a significantly thinner workpiece was cut than that cut during the training process. This caused a change in the process parameters and their increased variability because of the reduced stiffness of the workpiece, which was readily mirrored in the raising and increasingly variable Mahalanobis distances of the TIR moments of the signals collected during that time.

One can also note that the difference in Mahalanobis distances of the TIR moments between the two classes of machine operation considered in this paper, increases when a combination of sensors is used (Experiment 1 in Section 3.1), rather than when information from only a single sensors is employed (Experiments 2, 3 and 4 in Section 3.1). This improvement in the sensitivity of the classifier to a change in tool condition is even more visible in Figure 5. It is also apparent from experiments 2, 3 and 4 that the vibration and sound sensor signals show a higher sensitivity to lathe tool wear, when compared to that of the force sensor signal. This is in concordance with the conclusions of the study about appropriate sensor selection that ranked the force sensor sensitivity to lathe tool wear below those of the sound and vibration sensors, [19].

The experiments described in Section 3.2 demonstrate the ability of the classifier described in this paper to discriminate between a sharp and a worn tool once signals collected during machine operation with both a sharp and a worn tool have been presented to it during the training process. Results of these experiments reinforce observations made about the experiments from Section 3.1. Namely, Mahalanobis distances show a sharp change once a transition is made from one class of signals to another, and they apparently capture the change in process parameters that occurred when signals 40-48 were collected. Furthermore, one can see from Table 1 that the classifier performance improved and became perfect once information from multiple sensors was utilized.

5. CONCLUSIONS AND FUTURE WORK

In this paper, a new approach to machine degradation assessment and monitoring is proposed. It is based on the time-frequency signal processing tools and statistical pattern recognition. Several experiments with signals collected from sensors mounted on a CNC lathe machine are performed in order to demonstrate how this approach can utilize multiple sensor fusion to facilitate an increase in the sensitivity to the changes in the process parameters. Furthermore, the generic nature of the time-frequency and statistical pattern recognition tools allows the methods proposed in this paper to be applied to a variety of signals and situations, without significant human intervention, such as that necessary when CMAC based approach is used.

Nevertheless, further work is necessary to fully uncover and exploit the potentials of the methods proposed in this paper. Firstly, more signals must be collected under constant process parameters, and not with a significantly varying workpiece diameter, as was done when signals used in this paper were collected. Also, the Mahalanobis distances produced, as described in Section 3.3, should be statistically interpreted in order to assess the confidence index of the machine performance. Asymptotic normality of the time-frequency moments used in this paper can be employed in accomplishing this task. Finally, in order to fully demonstrate its abilities, the newly proposed approach should be tested in applications other than rotary machine monitoring. Possible areas of application are in welding, or gear-shift performance assessment and monitoring.

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