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Monitoring tool wear using classifier fusion

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ABSTRACT

Real time monitoring of manufacturing processes using a single sensor often poses significant challenge. Sensor fusion has thus been extensively investigated in recent years for process monitoring with significant improvement in performance. This paper presents the results for a monitoring system based on the concept of classifier fusion, and class-weighted voting is investigated to further enhance the system performance. Classifier weights are based on the overall performances of individual classifiers, and majority voting is used in decision making. Acoustic emission monitoring of tool wear during the coroning process is used to illustrate the concept. A classification rate of 87.7% was obtained for classifier fusion with unity weighting. When weighting was based on overall performance of the respective classifiers, the classification rate improved to 95.6%. Further using state performance weighting resulted in a 98.5% classification. Finally, the classifier fusion performance further increased to 99.7% when a penalty vote was applied on the weighting factor.

1. Introduction

The difficulty associated with tool condition monitoring during machining is primarily due to the continuous nature of tool wear. Several techniques have thus been investigated for estimating the tool condition [1–6]. A variety of classifiers have also been used for this purpose, and these include artificial neural networks [4,7–11], hidden Markov model [12,13], k-nearest neighbor [14], maximum likelihood, and support vector machine [15].

Since individual classifiers perform differently, depending on the type of application, the use of multiple classifiers has been investigated in some fields for making monitoring systems more robust [16–22]. Conceptually, this is similar to sensor fusion which capitalizes on the advantages of individual sensors and reduces sensitivity to noise [8,23–29]. Classifier fusion, on the other hand, capitalizes on the advantages of individual classifiers.

In earlier work on classifier fusion [30], a technique was investigated that evaluates the performances of a number of classifiers and selects the best among them using the concept of "overproduce and choose". This is similar in concept to the Fisher criterion [31], which is based on ranking of candidate process features.

In an application based on the modified Bagging method, the best of several artificial neural networks was selected for predicting the state of tool wear during drilling [32]. Another method for monitoring drilling operations was based on a decision fusion center algorithm [33]. Monitoring of the end milling process has also been investigated using machine ensemble techniques such as majority voting and generalized stacking [34].

Multi-classifier algorithms have often made use of a voting system, for example, majority voting [35,36]. However, as

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pointed out by Petrakos et al. [37], the results obtained using classifier fusion will not differ from that of a single classifier if the classifiers agree on class decision. On the other hand, voting plays an important role if the individual classifiers have different decisions. Another major challenge associated with voting is the issue of ‘tie votes’. This is often addressed using weighted voting [38,39] where the weights are normally constant. In situations where the classifier performances vary in the course of the process, such as may occur during tool degradation, then it becomes essential to account for such variation.

This paper extends the concept of decision fusion to classifiers, with a view to making tool condition monitoring systems more robust. This would enhance their performance by reducing classification errors that may result with individual classifiers. In addition, the state-performance weighting factor and penalty voting concepts are introduced to further improve classification rates.

Acoustic emission (AE) is used as the sensor signal, and the process investigated is the coroning process. Thus in Section 2, a brief background is provided on AE, the coroning process, and classifier fusion. This is followed in Section 3 by the experimental procedure. The results are presented and discussed in Section 4, and finally, the conclusions in Section 5.

2. Background

2.1. Acoustic emission (AE)

Acoustic emission refers to the elastic stress waves generated as a result of the rapid release of strain energy within a material due to a re-arrangement of its internal structure. Early applications of AE to machining can be traced to the work of Grabec and Leskovar [40], and Iwata and Moriwaki [41], who examined the fundamental characteristics of AE from machining. Subsequent work by Moriwaki [42] indicated that AE signals with large amplitude were associated with tool failures such as cracking, chipping, and fracture. Kannatey-Asibu and Dornfeld [43] later developed a relationship between AE and the cutting process. Good correlation was found between predicted and experimental results.

Emel and Kannatey-Asibu [44] monitored tool wear and breakage using pattern recognition analysis of AE signals generated during the process. In order to reduce cutting condition effects, an autoregressive analysis was used to model the acoustic emission signal sensed from the cutting process by Liang and Dornfeld [45]. Teti [46] presented experimental results for AE generation during machining of carbon steel using high speed steel tools under realistic cutting conditions. Blum and Inasaki [47] investigated both the force and AE signal generation during orthogonal cutting. A neural network consisting of two sequential learning stages, unsupervised Kohonen's feature map and input feature scaling was introduced by Leem et al. [4] for on-line monitoring of tool wear. High accuracy rates with robustness in the classifications of time and three levels of tool wear were achieved. In another application, AE was used to monitor both chatter and tool wear by Chiou and Liang [48].

A comprehensive summary of early work on AE monitoring of the machining process was presented in a review by Dornfeld [49] and Li [50]. Recent research in this field has focused more on micromachining operations [51–53]. Hung and Lu [53] modeled AE generation during micromilling, considering both the mechanics of the signal generation and propagation mechanisms. They accounted for the shear strain rate distribution on the shear plane and the dislocation density, considering a Gaussian probability density function for the distribution of AE source on the shear plane.

2.2. The coroning process

Coroning is a complex multi-dimensional metal removal process that is used for gear fabrication. Gears finished by polishing improve functional flank topology and reduce gear noise [54]. A coroning tool and system are shown in Fig. 1. It has a ring shape with teeth inside, which are coated with diamond. The tool is engaged with a gear and then rotates under pressure. In addition to the tool rotation, there is also simultaneous grinding action parallel to the rotation axis. Thus, the coroning process ensures final gear quality before its assembly in a transmission box. It has been used for transmission manufacturing, especially in volume production [54,55]. Such a mass production process requires a real-time monitoring system to ensure quality and productivity. However, tool condition monitoring (TCM) for the coroning process has not been reported in the literature.

2.3. Multi-classifier fusion

The fusion procedure for multiple classifiers [18,56,57] being considered here is illustrated schematically in Fig. 2, using the hidden Markov (HMM), Bayesian rule, Gaussian mixture (GMM), and K-means models [58,59].

We first define a matrix **B** consisting of the class pattern (decisions) determined by individual classifiers:

$$\mathbf{B} = \begin{bmatrix} b_{1,1} & b_{1,2} & b_{1,3} & \cdots & b_{1,m} \\ b_{2,1} & b_{2,2} & b_{2,3} & \cdots & b_{2,m} \\ \vdots & & & & \vdots \\ b_{n,1} & b_{n,2} & b_{n,3} & \cdots & b_{n,m} \end{bmatrix}, \quad b_{i,j} \in \{1, 2, 3, \ldots, N\} \tag{1}$$

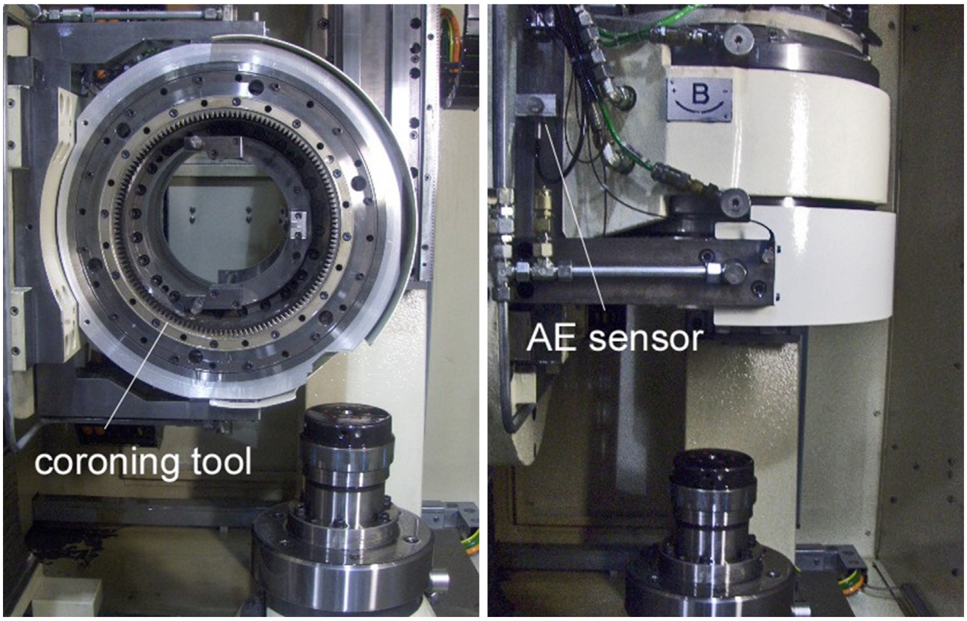

Fig. 1. Coroning machine and AE sensor attachment.

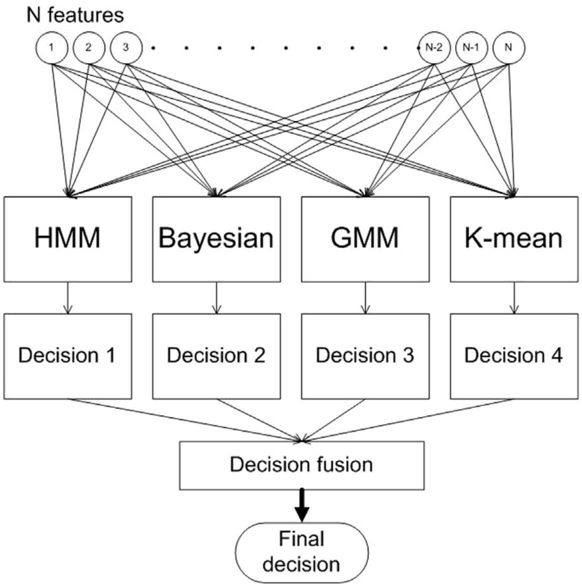

Fig. 2. Multi-classifier fusion.

where $b_{i,j}$ is the class pattern (decision) of observation j by classifier i

N is the number of classes or states.

m is the number of observations throughout the life of the tool.

n is the number of classifiers.

Now consider a weighting vector **W** that consists of individual classifier performances, w_i:

$$\mathbf{W} = [w_1\, w_2\, w_3 \cdots w_n] \tag{2}$$

where w_i is the performance of classifier i.

w_i is calculated for m observations as follows:

$$w_i = \frac{\sum_{j=1}^{m} \delta\left(b_{i,j}, y_j\right)}{m} \quad i = 1, 2, \ldots, n \tag{3}$$

where y_j is the true class of observation j, j =1, 2, 3, …, m

$$\delta(k, l) = \begin{cases} 1 & \text{if } k = l \\ 0 & \text{else.} \end{cases}$$

Before the final decision takes place, let us define the voting matrix V

$$\mathbf{V} = \begin{bmatrix} v(b_{1,1}) & v(b_{1,2}) & v(b_{1,3}) & \cdots & v(b_{1,m}) \\ v(b_{2,1}) & v(b_{2,2}) & v(b_{2,3}) & \cdots & v(b_{2,m}) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ v(b_{n,1}) & v(b_{n,2}) & v(b_{n,3}) & \cdots & v(b_{n,m}) \end{bmatrix} \tag{4}$$

where $v(i)$ is the ith row of the identity matrix, **I**, whose rank is determined by the number of classes of interest. For example, for a 3-class system (N=3), $b_{i,j}$ is then an element of {1, 2, 3}, and we have a 3×3 matrix **I**. Elements of **B**, $b_{i,j}$, are used to form the matrix **V**. For example, $v(b_{i,j})$ becomes [0,0,1] from the first row of the identity matrix, **I**, when $b_{1,1} = 1$. Likewise, $v(b_{n,m})$ becomes [0 1 0] when $b_{1,1} = 2$, and [0 0 1] when $b_{1,1} = 3$. Thus the voting matrix **V** is formed from the classifier decisions, $b_{i,j}$. The final decision equation is then the dot product of the weighting vector **W** and voting matrix **V**:

$$\text{Final decision} = \mathbf{D}_j = \left[\underset{column}{\arg\max} [\mathbf{W} \bullet \mathbf{V}(j)] \right] \tag{5}$$

where $\mathbf{V}(j)$ is the jth column of the voting matrix, **V**.

In the next section, we outline the experiments that were carried out to generate data for training and testing the monitoring system.

3. Experiments

The AE signal was used to monitor the coroning process, using the set up shown in Fig. 1, and data was collected at a 2 MHz sampling rate. A total of 2039 samples were collected, and approximately half of them were used as a training set for the classifiers. Additional details of the experimental set up are provided in [58]. The raw data was then converted to the frequency domain and frequency components were extracted as features. To identify a relationship between the tool condition and extracted features, the profile error of the fabricated gear was obtained by measuring profiles of gears reference to its tolerance using a coordinate measuring machine (CMM).

4. Results and discussion

Fig. 3 shows variation of two select features, 976 kHz and 483 kHz, and the profile error with number of parts produced (every 200th gear sample produced during the coroning operation). These two features were selected using the Fisher

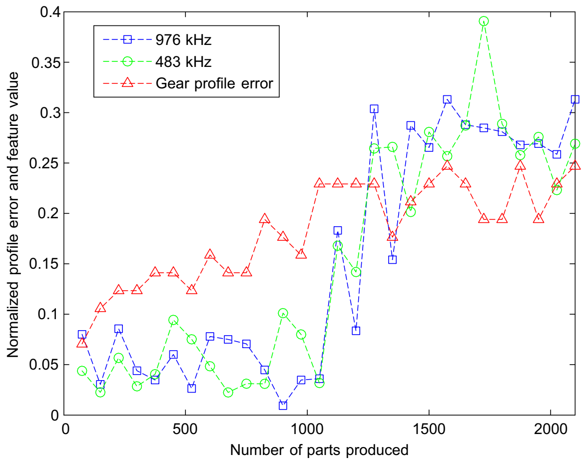

Fig. 3. Profile error measured and its comparison to select features (normalized spectrum amplitude at 976 and 483 kHz).

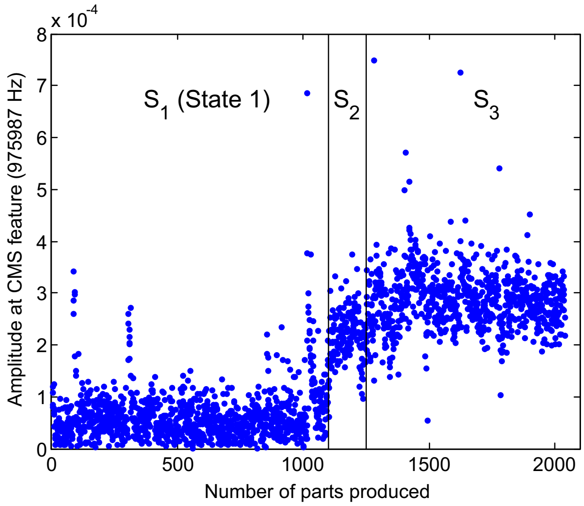

Fig. 4. Variation of the AE signal amplitude at 976 kHz with time (number of parts produced).

criterion [31,44] which ranks features based on their ability to separate the classes of interest. The plots show good correlation between the features and the profile error, and since the profile error is primarily due to tool wear, this indicates that monitoring the tool condition using these features will give an indication of gear quality. Since data was obtained from an actual production system, it was not feasible to obtain direct measurement of wear on the tool. Thus the number of parts produced was used as an indirect measure of wear, assuming a linear relationship between the two.

Since tool wear is a continuously varying process, we facilitate classification by categorizing the entire tool wear regime into three states: state 1 – sharp tool; state 2-slightly worn tool; and state 3-worn tool, Fig. 4. Fig. 5 shows a two dimensional feature space of these three states for two frequency features.

The features selected using the Fisher criterion, together with the tool condition, were used for training and testing the monitoring system. The overall performances of individual classifiers for monitoring continuous tool wear of the coroning process, Fig. 6, and the performances at each state, were then used as weighting factors in the classifier fusion algorithm. The performances of the four classifiers (hidden Markov model, minimum error rate Bayesian, Gaussian mixture model, and K-mean), were 94.1%, 94.1%, 84.0%, and 67.5%, respectively.

We now take an example to illustrate the influence of the weighting factor in the classifier fusion procedure outlined in Section 2.3 by comparing non-weighted and weighted decisions. Let us assume we have 4 classifiers, 5 observations, and 3 different states, which correspond to n=4, m=5, and $b_{i,j} \in \{1, 2, 3\}\ \forall$ i and j, with unity weight values and random class patterns. Then Eqs. (1)–(4) become:

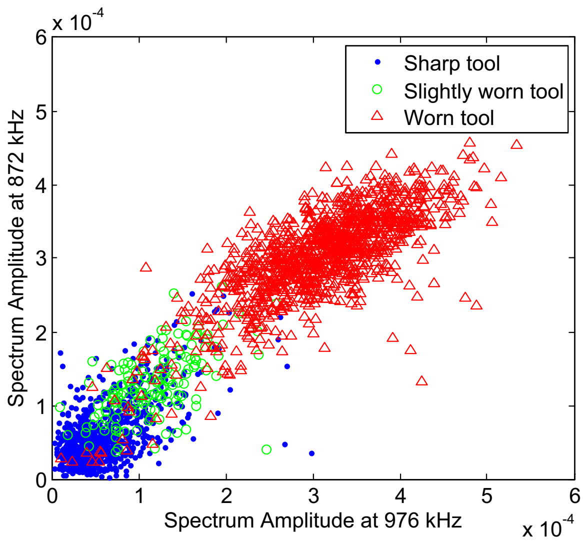

Fig. 5. State of cutting tool as represented by two frequency components in the feature space.

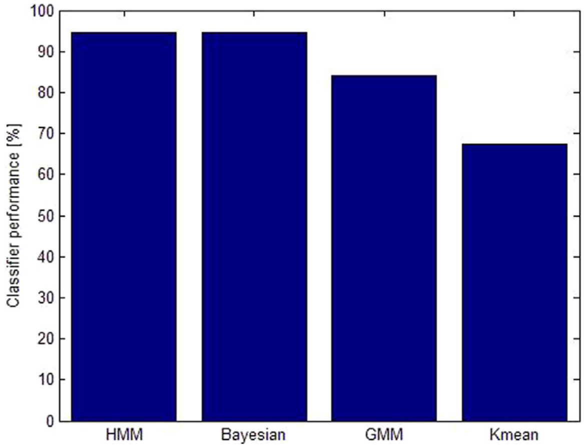

Fig. 6. Overall classification rates of individual classifiers for monitoring tool wear of the coroning process.

$$\mathbf{W} = [w_1 \;\; w_2 \;\; w_3 \;\; w_4] = [1 \;\; 1 \;\; 1 \;\; 1]$$

$$\mathbf{B} = \begin{bmatrix} b_{1,1} & b_{1,2} & b_{1,3} & b_{1,4} & b_{1,5} \\ b_{2,1} & b_{2,2} & b_{2,3} & b_{2,4} & b_{2,5} \\ b_{3,1} & b_{3,2} & b_{3,3} & b_{3,4} & b_{3,5} \\ b_{4,1} & b_{4,2} & b_{4,3} & b_{4,4} & b_{4,5} \end{bmatrix} = \begin{bmatrix} 2 & 1 & 2 & 3 & 3 \\ 1 & 1 & 2 & 2 & 3 \\ 1 & 1 & 1 & 3 & 2 \\ 1 & 2 & 2 & 3 & 2 \end{bmatrix}$$

And the voting matrix, V, becomes:

$$\mathbf{V} = \left[\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix} \right]$$

From Eq. (5), $\mathbf{W} \bullet \mathbf{V}(j)$ becomes;

$$\mathbf{W} \bullet \mathbf{V}(j) = \left[[3 \;\; 1 \;\; 0] \;\; [3 \;\; 1 \;\; 0] \;\; [1 \;\; 3 \;\; 0] \;\; [0 \;\; 1 \;\; 3] \;\; [0 \;\; 2 \;\; 2] \right]$$

Thus, the final decision becomes:

$$\text{Final decision } = [1 \;\; 1 \;\; 2 \;\; 3 \;\; 2 \;\; or \;\; 3]$$

In this particular example, there is a tie, as the final decision indicates. The weighting factor can play an important role in eliminating such situations by placing more emphasis on classifiers with higher weights. For example, the overall performances of individual classifiers for continuous tool wear using the experimental data, Fig. 6, are 94.1%, 94.1%, 84.0%, and 67.5% for the hidden Markov, minimum error rate Bayesian, Gaussian mixture, and K-mean models, respectively. These overall performances are used as weighting factors as follows:

$$\mathbf{W} = [w_1 \;\; w_2 \;\; w_3 \;\; w_4] = [0.941 \;\; 0.941 \;\; 0.84 \;\; 0.675]$$

Then from Eq. (5), $\mathbf{W} \bullet \mathbf{V}(j)$ becomes:

$$\mathbf{W} \bullet \mathbf{V}(j) = \begin{bmatrix} 2.456 & 0.941 & 0 \\ 2.722 & 0.675 & 0 \\ 0.840 & 2.557 & 0 \\ 0 & 0.941 & 2.456 \\ 0 & 1.882 & 1.515 \end{bmatrix}^T$$

resulting in the following final decision:

$$\text{Final decision } = [1 \;\; 1 \;\; 2 \;\; 3 \;\; 2]$$

which results in no more tie votes.

Since the individual classifier performances vary with the states, the classifier fusion concept can be further enhanced by updating the weighting factors using the respective classifier performances for each state. Three different types of weighting are investigated in this paper for tool wear monitoring of the coroning process. First, the overall performance of each classifier is used as a weighting factor as discussed in the preceding paragraphs. State performance, in other words class

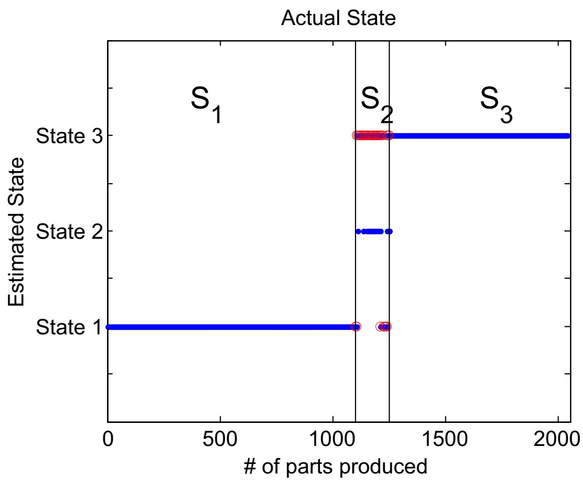

Fig. 7. HMM state estimation.

dependent performance, is discussed next. Finally, penalty accommodated weighting is used, and that gives a penalty on voting for classifier fusion in order to increase reliability.

In Fig. 6, most of the error for the HMM classifier came from state 2 as Fig. 7 shows.

Table 1 summarizes the results from single classifier performance in percentages. Among the single classifiers, the HMM and Bayesian show the best overall performance. However, in state 2, the classification rates were only 29.3% and 38.7% using HMM and Bayesian classifiers, respectively. Table 2 shows the results from classifier fusion with different weighting factors.

By applying the classifier fusion algorithm, the state 2 performance increased to 88% without a weighting factor, but the overall performance decreased to 87.7% compared to 94.1% without classifier fusion. Using weighted classifier fusion, with overall performance of individual classifiers as weighting factors, interestingly, the overall performance increased to 95.6% while the state 2 performance decreased to 51.3%. This is because the classifier performance is poor for the HMM and Bayesian classifiers in state 2, as Fig. 8 shows, but the weight was drawn from the overall performance, Fig. 6.

Since the HMM and Bayesian classifiers had better overall performance, these were overemphasized, leading to wrong decisions for state 2. Thus it is necessary to use the performance in each state as the weighting factors. The results were significantly improved when the state weighted factors were used, Table 2. The average classification rate increased from 95.6% to 98.5%, which is also higher than the single classifier performance of 94.1%.

It is observed from Fig. 9 and Table 3 that classifier fusion increased the overall performance. However, the non-weighted classifier fusion decreased performance when compared to HMM and Bayesian single classifiers.

State weighted classifier fusion increased overall performance, but it did not always improve the state performances. Classifier fusion with weighting factors enables more reliable decisions as a result of the high performance classifiers' voting. However, if three out of four classifiers have low performance, their combined effort could outweigh that of the high performing classifier, resulting in possible wrong decisions. To minimize this possibility, an adaptive classifier fusion with weighted voting is considered. A vote penalty is incorporated into the decision, resulting in the following weighting factor:

$$w_{f_i} = \begin{cases} w_i & \text{if } w_i \geq 95\% \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

Substituting w_{f_i} for w_i gives the results shown in Fig. 10. The penalty threshold can be determined based on the manufacturer's requirements.

Table 4 shows the improvement in classification using adaptive classifier fusion with 95% vote penalty based on classifier reliability.

Table 1
Single classifier performance (%) at each state.

	HMM	Bayesian	GMM	K-mean
State 1	100.0	99.2	90.8	97.1
State 2	29.3	38.7	98.7	92.0
State 3	99.7	99.0	71.6	21.6
Overall	94.1	94.1	84.0	67.5

Table 2
Classifier fusion performance (%) at each state.

	Classifier fusion (No weight)	Classifier fusion (Overall weight)	Classifier fusion (State weight)
State 1	99.2	99.2	99.2
State 2	88.0	51.3	91.3
State 3	71.6	99.0	99.0
Overall	87.7	95.6	98.5

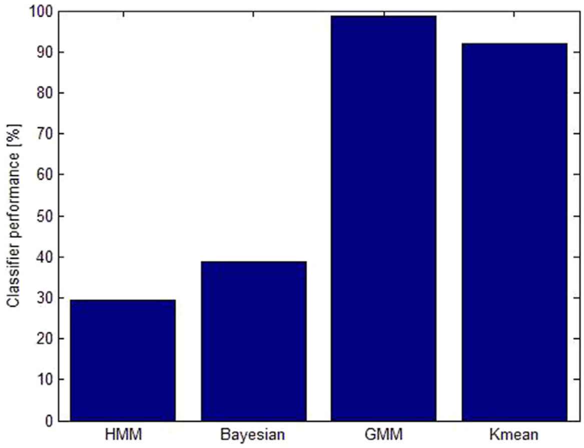

Fig. 8. Classification rates of individual classifiers for monitoring the coroning process in state 2 (slightly worn tool).

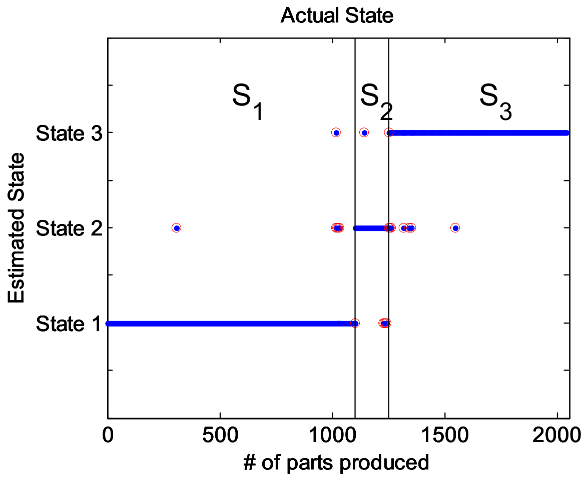

Fig. 9. Classification results based on classifier fusion (state weighted majority vote).

Table 3
Single classifier vs. classifier fusion with weighted majority vote.

	HMM	Bayesian	GMM	K-mean
Single classifier	94.1	94.1	84.0	67.5
Classifier fusion (majority vote)	87.7			
Classifier fusion (overall weighted majority vote)	95.6			
Classifier fusion (state weighted majority vote)	98.5			

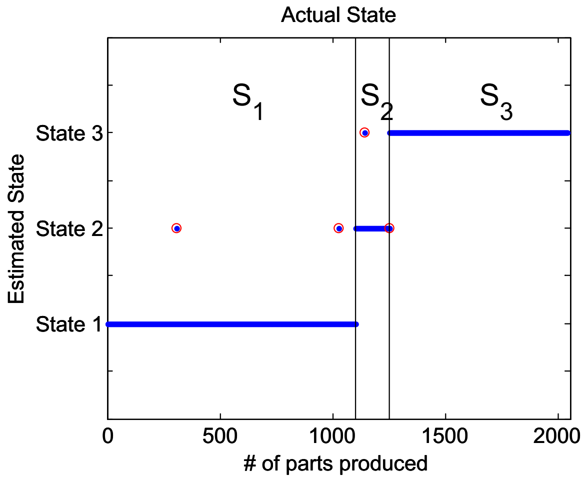

Fig. 10. Adaptive classifier fusion with state weighted vote penalty.

Table 4
Adaptive classifier fusion compared to classifier fusion.

	Classifier fusion (State weight)	Adaptive classifier fusion (State weight vote penalty)
State 1	99.2	99.8
State 2	91.3	98.7
State 3	99.0	99.7
Overall	98.5	99.7

5. Conclusions

A classifier fusion algorithm adapted from decision fusion significantly increased performance compared to the non-fused algorithm in monitoring tool wear during coroning. Even though the overall monitoring performance improved with the new technique, the performance for some states improved at the expense of others. This trend was eliminated by applying an adaptive classifier fusion, where a vote penalty was introduced, preventing multiple wrong votes, and this improved classification rate from 98.5% to 99.7%.

Even though the technique was demonstrated for acoustic emission monitoring of the coroning process, it should also be applicable to any process of interest, using any suitable sensors.

Acknowledgments

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Appendix

Following is a summary of the four classifiers used in the analysis [58, 59].

Hidden Markov model

The model may be represented in compact form as ($\mathbf{g} = \mathbf{P}, \mathbf{Q}, \mathbf{z}$) such that:

- a finite set of N states is given by $\mathbf{S} = \{S_1, \cdots, S_N\}$and the state at time t is o_t
- $\mathbf{P}$ is a $N \times N$state transition probability matrix
- $\mathbf{Q}$ is the probability distribution of observation, with elements $q_j(\mathbf{x}_t)$,

where $\mathbf{x}$ is a sequence of observations: $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_t$

$\mathbf{x}t$ represents an observation at time t

- an initial state probability distribution is expressed as $z = \{z_i\}$, where z_i is the probability that $o_1 = S_i$, $1 \le i \le N$.

The state $\hat{o}_t$ can be estimated through an a posteriori probability, which can be found using Bayes' rule.

Minimum error rate Bayesian classification

This classifier is based on the criterion that an observed signal should be assigned to:

S_i if $p\,(\mathbf{x_t}|S_i)\,P(S_i) > p\,(\mathbf{x_t}|S_j)\,P(S_j)$

where S_i represents state or class i

$p\,(\mathbf{x_t}|S_i)$ = likelihood of $\mathbf{x_t}$ given S_i
$P\,(S_i)$ = a priori probability of class i.

If the class conditional probability density function is assumed to have a normal distribution, then each class can be shown to be given by the discriminant function:

$$g_i(\mathbf{x}) = -\frac{1}{2}\left(\mathbf{x}_t - \mu_i\right)^T \Sigma_i^{-1}\left(\mathbf{x}_t - \mu_i\right) - \frac{d}{2}\ln(2\pi) - \frac{1}{2}\ln|\Sigma_i| + \ln P(S_i)$$

where d is the dimension of vector $\mathbf{x_t}$

$\boldsymbol{\mu}_i$ is mean of class S_i
$\boldsymbol{\Sigma}_i$ is the covariance matrix of class S_i.

Gaussian mixture model

Assuming a Gaussian distribution, this model determines the mixtures which maximize the likelihood of n samples of N different group clusters $(N < n)$, $S = \{S_1, S_2, \cdots, S_N\}$ with starting means $K = \{\mu_1, \mu_2, \cdots, \mu_N\}$. Given a set of observations$(\mathbf{x_1}, \mathbf{x}_2, \cdots, \mathbf{x}_t)$, the likelihood function, L, can be expressed as:

$$L = p\,(\mathbf{x_1}, \mathbf{x_2}, \cdots, \mathbf{x_t}|S_i) = \prod_{i=1}^{n}\sum_{i} p\,(\mathbf{x}_i|S_i, \mu_1, \mu_2, \cdots, \mu_N)\,P(S_i)$$

This is maximized such that $\frac{\partial L}{\partial \mu_i} = 0$.

K-means

K-means involves assigning a set of samples to the closest mean vectors, μ_i, for a finite set of N states. Given a set of observations $(\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_t)$, K-means minimizes the within-cluster sum of squares:

$$\arg\min_{S}\sum_{i=1}^{N}\sum_{\mathbf{x}_j \in S_i}\|\mathbf{x}_j - \mu_i\|^2$$

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